BEYOND CARBON MITIGATION: UNDERSTANDING THE CO-BENEFITS AND CO-COSTS OF GREENHOUSE GAS MITIGATION POLICIES IN BROADER CONTEXTS

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BEYOND CARBON MITIGATION: UNDERSTANDING THE CO-BENEFITS AND CO-COSTS OF GREENHOUSE GAS MITIGATION POLICIES IN BROADER CONTEXTS

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SUMMARY

The use of cost-benefit analysis (CBA) is firmly entrenched in U.S. policy-making and other regulatory processes. The validity of CBA relies on the systematic and comprehensive understanding of the co-benefits and co-costs associated with the public policy evaluated. However, we still don't have a complete picture or a thorough understanding of the broader impacts of public policies on energy and the environment, especially carbon mitigation policies. Notably, the recent developments from the federal governments have attracted more attention to revisiting the concepts.

To address the gaps in understanding the broader impacts of energy policies, this dissertation expands existing research on energy and environment policies by providing more empirical evidence and advanced systematic quantification frameworks. In general, this study highlights critical relationships in intricate modeling systems, thereby enabling insights that might otherwise be obfuscated or overlooked. By applying complex integrated models of energy policies, climate systems, and health evaluations, this dissertation enhances a better understanding of the complexity of features that influence policy markets in the energy-related economy. The three case studies cover the systematic and comprehensive quantifications of co-benefits and co-costs in various sectors and scopes (air quality and health, sectoral and macroeconomic activities).

The first study applies integrated macroeconomics and air quality model to evaluate the unintended environmental consequences of relaxing the energy policies on the ozone standard attainments. The results demonstrate that a relaxation of the energy policies would significantly increase the ozone levels in many counties, inducing considerable health costs. The impacts are more prominent when considering the synergistic effect of dramatic climate change. Overall, the

study demonstrates the critical need to conduct assessments of energy policies in the context of local air quality and associated health benefits and costs.

The second study focuses on a case of the sectoral economic activities – quantifying the impacts of electric vehicle mandates on grid operations under the current infrastructures and grid management practices of the electric power sector. This chapter explores the benefits and costs of EV-related policies on the electric power grid when the infrastructures are locked-in, and the technological innovations are limited in practice. The third study expands the scope to demonstrate the long-term societal macroeconomic impacts, quantifying the effects of the EV sales mandates beyond the direct impact on the transportation sector and the electric power sector, including the indirect and induced impacts on all sectors through macro-economic activities. Overall, the two studies indicate significant potentials for the grid and other sectors to adapt and reduce both the costs and carbon emissions. The results call for policymakers to move beyond sectoral narratives, adopt a holistic and systematic view, and design policies with great care to address the regional heterogeneity and equity concerns.

CHAPTER 1. INTRODUCTION

1.1 Background

Discussions about the impacts of energy and environmental-related regulations have been a part of the public dialogue since the beginning of the US EPA (Arrow et al., 1997; Hahn & Dudley, 2007). These impacts need to be well-understood and quantified to facilitate the cost-benefit analysis, which has been adopted and widely used not only as a requirement of federal regulations but also for better policy design and justification purposes – to help the energy-related policies to gain more support in the policy arena and avoid too much market distortions (Adlert & Posnertt, 2011; Arrow et al., 1997).

In the U.S., since 1981, following the two executive orders from President Reagan and President Clinton both requiring agencies to prepare Regulatory Impact Analysis (RIA) for all major federal regulations, cost-benefit analysis has been routinely used by U.S. government agencies (Adlert & Posnertt, 2011; Arrow et al., 1997). Both executive orders mentioned that all significant costs and benefits should be included when doing a cost-benefit analysis. Correspondingly, they also issued the guidelines for conducting cost-benefit analysis for the US EPA and U.S. OMB. (US EPA, 1983; US OMB, 1996).

Recently, the debates have been more controversial when carbon dioxide mitigation becomes a new goal for the policy designs. For one thing, compared to the traditional criterion pollutant controls, the greenhouse gas mitigation policies face more significant challenges from the complexities of understanding their boarding impacts, including co-benefits and co-costs, let alone to quantify them concisely (Aldy et al., 2010; Deng et al., 2017; Helgenberger et al., 2019).

The divergence of the US EPA regulations under the Trump administration from the other administrations has drawn more attention to the co-benefits and co-costs discussions. The Trump administration put on more restraints on the considerations of co-benefits and co-costs when doing cost-benefit analysis in environmental contexts. In repealing the Clean Power Plan proposed by the Obama administration, the Trump administration proposed to price the social cost of carbon at about $5.5/ton, which are only limited to consider directly impacts occurring within U.S. borders (US EPA, 2019b). In addition, US EPA under the Trump administration also revised the Supplemental Cost Finding for the Mercury and Air Toxics Standards (the MATS rule) and the Clean Air Act (CAA) required risk and technology review (RTR), arguing that the co-benefits should not be included in the cost-benefit analysis since they do not relate to the primary purpose of the Clean Air Act (US EPA, 2019a).

These recent updates have discussed (mostly questioned) from various perspectives - from the legal provisions of the Supreme Court on environmental laws to the logic of cost-benefit analysis and the fundamentals of public policymaking (Dedoussi et al., 2019; Graham et al., 2019; Jonathan S. Masur, 2019; Madhu Khanna, Xiaoguang Chen, 2019). This discussion calls for a broader and deeper understanding of the co-benefits and co-costs, especially under the new development under the Biden administration, revisiting and signaling to raise the social cost of carbon back to $51/ton, the level used before the Trump administration.

Meanwhile, beyond the controversies in the U.S., the international communities and organizations, for example, the IPCC and the World Bank, have made substantial efforts into the comprehensive studies on the impacts of carbon emissions to include wide ranges of the co-benefits and co-costs (IPCC, 2014; The World Bank, 2010). According to IPCC, the co-benefits is defined as “the positive effects that a policy or measure aimed at one objective might have on other objectives, irrespective of the net effect on overall social welfare" and co-costs or adverse side effects as 'The negative effects that a policy or measure aimed at one objective might have on other objectives, irrespective of the net effect on overall social welfare' (IPCC, 2014). In particular, these reports emphasize the necessity and importance of understanding co-benefits and co-costs (Deng et al., 2017). The more systematic and comprehensive understanding will help the researchers and policymakers to identify the types of benefits or costs to consider and their geographic focus, improve the treatments of the heterogeneity of the co-benefits (Deng et al., 2017), design appropriate data collection methods, and data requirements (Anadon et al., 2016), and inform different levels of negotiations (Pittel & Rübbelke, 2008). In addition, understanding the co-benefits of green house gas (GHG) mitigation policies can also serve as a way that may help increase the political viability of stronger climate mitigation efforts by emphasizing benefits that may be closer to the decision-makers, the individual voters, or firms (Deng et al., 2017).

However, the existing literature and studies on co-benefits and co-costs of the GHG mitigation policies are incomplete in many critical issues. In a review, Deng et al. summarized more than 1500 articles published on the co-benefits of carbon mitigation policies internationally and found that the previous studies have focused on limited fields using limited research methods (as shown in Figure 1-1, from Deng et al., 2017). The main co-benefit types are concentrated on the ecosystem, economic analysis, and air pollution & health impacts. Besides, these types of co-benefits are mainly demonstrated within limited sectors – agriculture and forestry (31.6%), electricity (24.7%), transportation (10.2%) (Deng et al., 2017).

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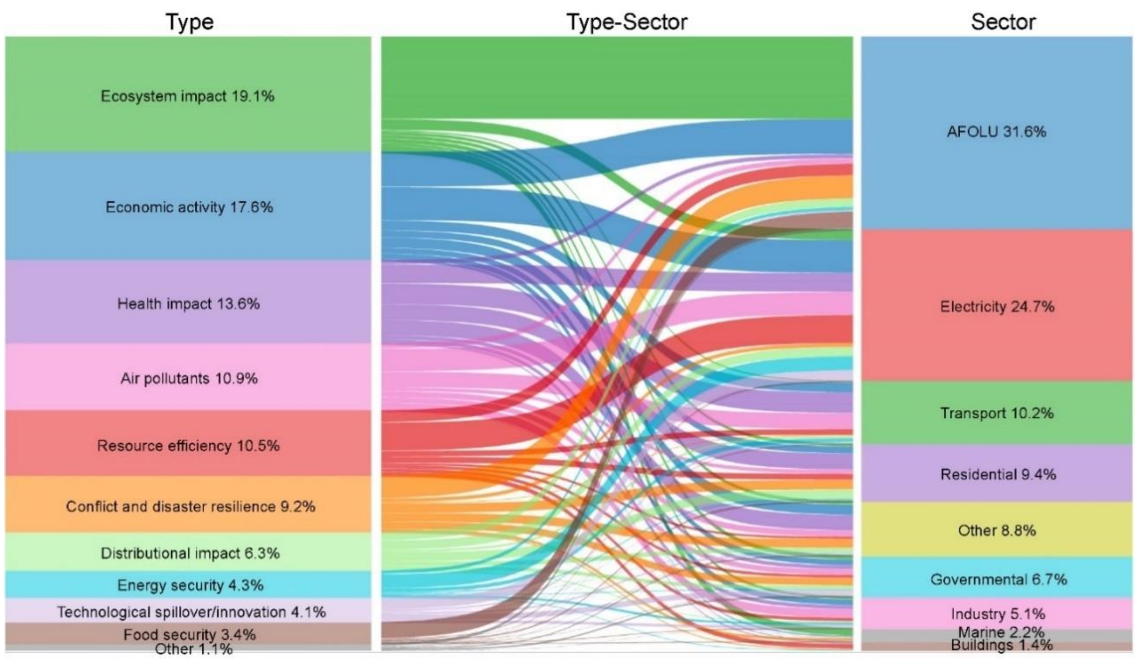


Figure 1-1 Co-benefit types in different mitigation sectors

The width of the lines connecting a particular co-benefit (left-hand side column) with mitigation in a particular sector (right-hand side column) is proportional to the number of papers studying that issue (Deng et al., 2017). AFOLU refers to agriculture, forestry and other land-use sectors.

Surprisingly, despite the extensive scholarship on the co-benefits and co-costs of GHG mitigation policies, there are two major drawbacks in the current understanding. On the one hand, many of these significantly focused research areas have not formed comprehensive quantification frameworks. While on the other hand, some co-benefits and co-costs of the GHG mitigation policies have been little researched and scarcely mentioned. These two research gaps are explained further when examining the specific types of co-benefits and co-costs, such as health and air quality and macro-economic activities.

First, the co-benefits of air pollution and health impacts are the primary concerns in most governmental discussions and arguably the most important (Deng et al., 2017; Helgenberger et al., 2019; IPCC, 2014). However, the complex effects of environmental policies and the uncertainties associated with future climate have hindered concise quantifications in the previous literature. For example, scarce studies have shown some detailed mechanisms of the synergies between the GHG mitigation efforts and the air pollution control (Lam, Fu, Wu, & Mickley, 2011; Lin, Patten, Hayhoe, Liang, & Wuebbles, 2008). A quantitative framework has not been available that considers the effects of all these relevant factors,i.e., changes in meteorology, increases in atmospheric CO_2, biogenic emissions (both direct and indirect impacts), on future pollution.

Second, the macro-economic activities need to be better understood, especially considering the recent development of the transportation and electric power sectors, such as the massive electric vehicle adoptions and the EV-grid interactions coupled with substantial renewable generation resources. The impacts of the EVs on the electric power sector management have been projected to be considerable but poorly understood (Al-Alawi & Bradley, 2013a; Bernardo & D'Alessandro, 2016; Cai et al., 2014a; Noori & Tatari, 2016; Richardson, 2013; Tan et al., 2016a). Currently, a large number of the analysis has focused on the short term sectoral economic impacts when the grid is operated under the current infrastructures and grid management practices without any coordination or technological innovations between transportation sector and the electric grid (Alizadeh et al., 2016; Rahbari-Asr et al., 2016; Umeano, 2016 Anastasiadis et al., 2019; Elgowainy et al., 2018). However, these studies have shown little consensus in either completing quantification frameworks or settling down the final monetizing estimates, which calls for further research.

The macro-economic activities need further scrutiny when considering the long-term broader impacts of electric vehicle policies on grid operation cost, electricity rates, and consumer bills with capacity planning, coordinated charging, and other ancillary services. An example is to examine the more complex grid-EV integrations, like V2G development (Fasugba & Krein, 2011; Kempton & Tomić, 2005; Noel & McCormack, 2014; Parsons et al., 2014; Shinzaki et al., 2015; D. Wang et al., 2016). Previous studies have shown the potentials to lower the cost of operations and the total carbon emissions by capacity planning and other EV-grid coordination strategies, including three areas:

- Ease other renewable energy policies compliance, lower the overall cost, customer's burden (Brwon et al., 2019; Jiang, 2017; Wu et al., 2014; Dong et al., 2013)
- Facilitate emission reduction potentials (Brwon et al., 2019; Wu et al, 2019; Elgowainy et al., 2018; Edelenbosch et al., 2018; Harley, 2007)
- Allow more renewable generation (Hai et al., 2019; Atia et al., 2015; Fiori et al., 2016; Melton et al., 2016; Edelenbosch et al., 2018; Schneider et al., 2006)

Most of these studies are done either for the U.S. in general (Brown & Soni, 2019; Wolbertus et al., 2018; Sovacool et al., 2017; Xie et al., 2019; Almutairi et al., 2018; Tan et al., 2016; Fitzgerald et al., 2016; Sovacool & Hirsh, 2009) or using IEEE simplified simulation systems (Hashemi et al., 2018; Zhang et al., 2018; Alizadeh et al., 2016; Rahbari-Asr et al., 2016; Umeano, 2016; Su et al.,, 2014; Marols et al., 2014; Buekers, Van Holderbeke, Bierkens, & Int Panis, 2014; Han et al., 2015; Anastasiadis et al., 2017). Scarce of these studies focus on sub-country regional levels. Some of the limited existing regional studies (Brown et al., 2017; Buhanist, 2015; Onufrey & Bergek, 2015; Buhanist ,2015; Wolsink ,2012) show great heterogeneity of the regions response and ability to alter their grid management practice, which calls for more research and understanding. Many of these research also illustrates certain path dependences traits when the regions are self-reinforcing and lock in their policies, infrastructures, and behaviors (Brown et al., 2017; Buhanist, 2015; Onufrey & Bergek,2015). However, these aspects of the co-benefits and co-costs are little researched before, let alone quantified systematically.

1.2 Motivations

To address the gaps in existing research in understanding the broader impacts of energy policies, my thesis enhances the understandings of the co-benefits and co-costs for the GHG mitigation policies by addressing several critical unsolved issues. The dissertation does not aim to provide a full picture of listing all the co-benefits and co-costs associated with one policy or certain types of policies. Instead, it contributes to the quantification frameworks by filling some of the missing puzzles unsolved to tackle today's green transitions. The study adopts more systematic and comprehensive quantifications of co-benefits and co-costs in various scopes, providing case studies on different types (air quality and health, and sectoral and macroeconomic activities) of the co-benefits or co-costs.

In sum, the motivations of this dissertation are to understand better the fundamental concepts of the co-benefits and co-costs related to GHG mitigation policies, linking GHG mitigation policies to their broader impacts, and facilitating better frameworks for quantifications. To be specific, the study will focus on a U.S. territory focus and include recent developments on the following three aspects to enhance the understandings of co-benefits and co-costs (Figure 1-2.):

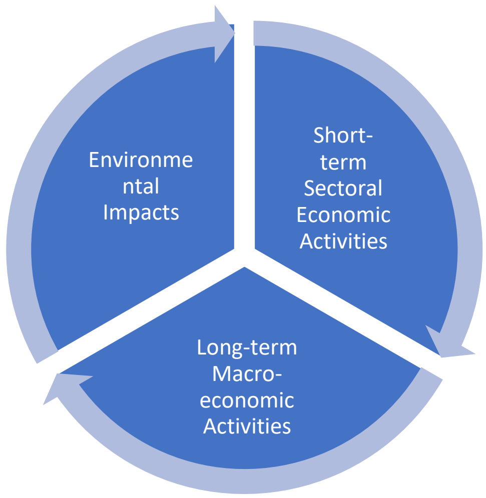


Figure 1-2 Aspects of the co-benefits and co-costs of the carbon mitigation policies focused in my thesis

First, my thesis constructs a quantification framework for measuring the co-benefits and the co-costs of air pollution and health impacts. Taking one of the most influential but challenging pollutions, tropospheric ozone, as an example, this chapter introduces a more systematic and comprehensive integrated model framework to measuring the co-benefits and co-costs of ozone controls of the clean energy policies.

The second study focuses on a case of the sectoral economic activities – quantifying the impacts of electric vehicle adoptions on grid operation costs under the current infrastructures and grid management practices of the electric power sector. This chapter explores the benefits and costs of EV-related policies on the electric power grid when the infrastructures are locked in and the technological innovations are limited in practice.

Last, the third study further examines the broader long-term macro-economic impacts from a case study evaluating the effects of the EV-related policies on the general economy in the long term. In this case study, the effects of EV mandate policies are identified and evaluated, providing a comprehensive framework for quantification of long-term macro-economic co-benefits and co-costs resulted from EV adoptions. It considers different types of benefits - the grid operation cost, electricity rates, and consumer bills. The electric power sector plays an active role in adjusting its infrastructures through capacity planning and leveraging technological breakthroughs to adapt to innovative grid management practices in the long run. In addition, this chapter also explores the regional heterogeneity by comparing the results between three different territories of the U.S. - the New York, California, Southeast territory, which differ in their electricity market regulation status, grid management practices, the potential generation resources available. The analysis explores the regional heterogeneity in different U.S. territories and illustrates the need to adjust quantification frameworks specifically to the regions and provide policy designs correspondingly.

The remainder of this dissertation is organized as follows. Chapter 2 explores the effect of co-benefits in environmental pollution controls - relaxing energy policies coupled with climate change will significantly undermine efforts to attain U.S. ozone standards. Chapter 3 looks at a short-term, sectoral macro-economic development case study - how electric vehicles induce co-costs and co-benefits on grid operations for three example regions. Chapter 4 examines another case of the long-term macro-economic impacts of electric vehicle policies on the grid operation cost, electricity rates, and consumer bills nationwide and regionally, considering the options of the coordinated charging and other ancillary services through V2G technologies. Lastly, the final chapter summarizes key findings from the three essays and provides a future set of recommendations.

CHAPTER 2. ENVIRONMENTAL IMPACTS CASE STUDY: THE IMPACTS OF RELAXING ENERGY POLICIES ON THE ATTAINMENT OF THE U.S. OZONE STANDARDS

Federal agencies in the Trump administration have sought to relax the energy policies (EPs), which are expected to increase emissions not only of greenhouse gases but also conventional air pollutants, potentially leading to a deterioration of air quality, including increases in the ground-level ozone (O_3). In this study, an integrated modeling framework was applied to show that compared to a scenario with the continued EPs and with a stationary climate, a relaxation of EPs coupled with intense warming will significantly increase the number of U.S. counties in non-attainment for O_3 by 2050, potentially increasing control costs up to several billion dollars. This result has demonstrated the synergistic effects of EP relaxation and climate change on O_3 standard compliance, resulting from the increases in O_3 production efficiency under climate warming. Thus overall, the study shows that the interactions of conventional air pollutant emissions with climate feedbacks should be considered and integrated when addressing the air quality co-benefits and co-costs of EPs.

2.1 Introduction

Tropospheric ozone (O_3) is an important greenhouse gas (GHG) and air pollutant, which is detrimental to human health, vegetation growth, and ecosystem productivity (Monks et al., 2015; US EPA, 2006). Globally, O3 air pollution is associated with over 200 thousand premature deaths and crop production losses of approximately 100 million metric tons every year (Avnery et al., 2011; Cohen et al., 2017). Decades of efforts to reduce air pollutant emissions have improved air quality in the United States (U.S.) with arguably tremendous benefits for human and ecosystem health(Avnery et al., 2011; Monks et al., 2015; US EPA, 2006). However, these mitigation experiences have proved that O_3 is one of the most difficult criteria air pollutants to regulate. Approximately 30% of the U.S. population resides in counties designated as O_3 nonattainment, more than any other criteria air pollutant(US EPA, 2016). In 2017, 51 areas (or 126 out of 730 monitored counties) were in nonattainment status under the 2015 National Ambient Air Quality Standards (NAAQS) for O_3 (0.070 ppm for the three-year average of the annual fourth-highest maximum daily average 8-hour O_3 concentration, or MDA8h O_3) (US EPA, 2016). The NAAQS for O3 are reviewed periodically and have been tightened twice since 1997(US EPA, 2016). The last review considered tightening the standard even further to 0.060 ppm as evidence indicates that adverse health effects are associated with exposure to O_3 at such low levels (Crouse et al., 2015; Di et al., 2017; Kim et al., 2011). Each time O_3 standards are tightened, states must spend billions of dollars more to achieve attainment(Lange et al., 2018). Although current regulations are expected to lead to continuing reductions of ground-level O_3 concentrations, such mitigation efforts may be counteracted by 1) the recent relaxation of energy policies (EPs) that may increase anthropogenic emissions of O_3 precursors such as nitrogen oxides (NOx) from fossil fuel combustion (Tollefson, 2018), and 2) climate change which may aggravate O_3 due to the climate penalty that is likely to increase O_3 production under warming (Jacob & Winner, 2009).

Recent rules and proposals within the first three years under the Trump administration seeked to relax several EPs and associated regulations designed to mitigate climate change, e.g., replacing the Clean Power Plan (CPP) with the Affordable Clean Energy (ACE) rule and freezing the Corporate Average Fuel Economy (CAFE) standards(The Safer Affordable Fuel-Efficient (SAFE) Vehicles Rule for Model Years 2021–2026 Passenger Cars and Light Trucks., 2018).

These policy changes will result in increased consumption of fossil fuels and higher emissions of GHGs and are also expected to increase emissions of conventional air pollutants (hereafter referred to as "air pollutants") that are linked to O_3 formation(Driscoll et al., 2015; Keyes et al., 2019). The relationships between EP relaxation and air pollutant emissions are driven not only by regulatory requirements but also by changing markets and interactions among energy-related sectors (Burtraw et al., 2003; Thompson et al., 2014), making subsequent impacts on ground-level O_3 unclear. Moreover, EPs are usually implemented several years after the initial proposal. Their effects could persist for decades, over which the environmental conditions influencing O_3 formation (e.g., other domestic and global emissions and meteorology) can significantly change.

Climate change will likely counteract efforts to mitigate ground-level O_3 via multiple processes, including 1) direct meteorological impacts on the transport, deposition, and photochemistry of O_3, and 2) indirect impacts via changing biogenic emissions. Increases in temperature (warming) alone, will challenge O_3 mitigation due to the temperature-dependent nature of both the photochemical formation of O_3 and the peroxyacetyl nitrate (PAN) reservoir of NOx (Jacob & Winner, 2009; US EPA, 2006). Future changes in other meteorological factors, such as increasingly stagnant air and changes in water vapor and solar radiation, will also likely play a role in modifying O_3 levels at local to regional scales (Jacob & Winner, 2009; US EPA, 2006).

Biogenic emissions are a major atmospheric source of non-methane volatile organic compounds (BVOCs, a group of O_3 precursors)(Kesselmeier & Staudt, 1999). Recent evidence suggests the growing importance of BVOCs to VOC reactivity and ambient O_3 levels as anthropogenic emissions decline(Chen et al., 2019). However, the effects of climate change on future BVOC emissions are less certain. BVOC emissions are expected to increase due to warming but will be inhibited due to increases in atmospheric CO_2 (A. B. Guenther et al., 1993; Wilkinson et al., 2009). Increases in BVOC emissions could partly result from potential increases in leaf area index (LAI, the one-sided green leaf area per unit ground surface area)(Heald et al., 2009). Given a constant emission rate (i.e., the amount of BVOCs emitted per unit leaf area), increases in LAIs will proportionally increase BVOC emissions. This response is a direct impact of increases in LAIs. However, indirect effects of increases in LAIs can also occur due to decreases in leaf temperature and attenuation of photosynthetically active radiation through the canopy, thus decreasing BVOC emissions (A. Guenther et al., 2006). While a few studies have shown the importance of BVOC emissions in modifying ground-level O_3 under climate change (Lam et al., 2011; Lin et al., 2008), a quantitative framework has not been available that considers the effects of all these relevant factors,i.e., changes in meteorology, increases in atmospheric CO_2, and increases in LAIs (both direct and indirect impacts), on future O_3 pollution.

2.2 Motivation and research questions

To close the gap in the existing quantification framework, this study assesses the existence and the magnitude of the impacts of GHG mitigation policies on air pollution, taking ozone emission as an example. It considers the complex pathways and driving factors in evaluating the impacts of EP relaxation and climate change on ground-level O_3 in 2050 over the contiguous U.S. (CONUS). Focusing on the attainability of O_3 standards, this evaluation allows us to target days with high O_3 levels associated with significant adverse impacts on human health. Based on an integrated modeling framework, I explore that the impacts of EP relaxation and climate change on O_3-standard attainability are interactive and can be visualized with an isopleth diagram.

2.3 Hypotheses

The costs of EP relaxation should consider the adverse effects on human and ecosystem health associated with O_3 exacerbation that is caused by direct pollutant emission changes from energy consumption, indirect climatic feedbacks from EP-induced climate change, and synergistic effects between emission and climate. Based on the current review, I propose the hypotheses here:

Hypothesis 2.1: The continuation of the EP policies will significantly ease the difficulties of ozone standard attainment. While on the other hand, Relaxing energy policies would reverse a current trend in decreasing ground-level ozone, increasing the number of non-attainment counties and related health costs.

Hypothesis 2.2: The synergistic effect of the energy policies with climate change exists – under the situations of more aggressive climate change, EP policies will have higher benefits in ozone standard attainment, thus reducing overall health costs.

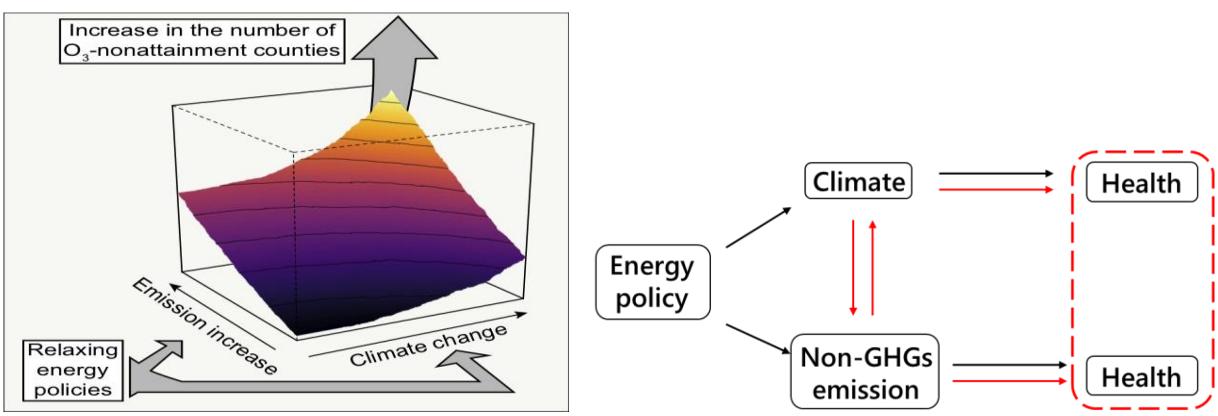


Figure 2-1 General framework: interactions of energy policies, climate and non-GHG emissions on health

2.4 Methodology

I use a multi-sectoral computational general equilibrium model, GT-NEMS (Brown & Li, 2019), combined with two EP scenarios, EP-CONT and EP-RELX, to explore the effect of EP relaxation on energy consumption through 2050. To achieve this goal, first, I use a bottom-up method to calculate pollutant emissions from the energy consumption projected by GT-NEMS. The emission inventory consists of 50 energy consumption sources in total (Table S2). In addition, I conduct six sets of sensitivity tests by using alternative baseline assumptions in GT-NEMS to evaluate the responses of emissions to the assumption changes. Detailed information on the background and model configurations of GT-NEMS, the EP scenarios, emission estimation, and the sensitivity tests is provided in Supplemental Experimental Procedures, Figure S6, Figure S10, Figure S11, and Data S1. At last, I estimate the monetized impacts of the ozone concentration changes modeled.

The details of the modeling framework are explained in the following section.

2.4.1 General structure of the integrated modeling framework

The integrated modeling framework consists of the Community Multiscale Air Quality model with the high-order decoupled direct method (CMAQ-HDDM) (Cohan et al., 2005), the National Energy Modeling System operated by the Georgia Institute of Technology (GT-NEMS)(Brown & Li, 2019), climate projections from the Community Earth System Model (CESM) (Monaghan, A. J., Steinhoff, D. F., Bruyere, C. L., & Yates, 2014), and biogenic emission estimates via an updated version of the Biogenic Emission Inventory System (BEIS)(Bash et al., 2016) (See Experimental Procedures and Supplemental Experimental Procedures for details). I consider the current O_3 standard level (0.070 ppm) as well as a tighter level (0.060 ppm) for assessment purposes. EP relaxation and climate change are set as two independent components affecting O_3 — EP relaxation affects anthropogenic emissions, while climate change affects meteorology and biogenic emissions. Also, the direct impact of EP relaxation on climate change is not assessed in this study. Last, I also explore the monetized impacts of the ozone concentrations change triggered by relaxing EPs.

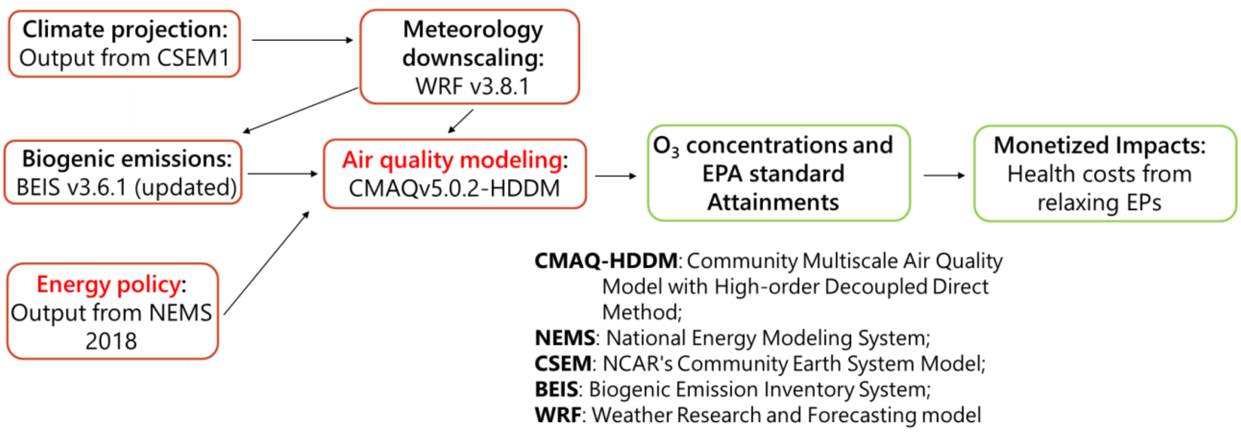


Figure 2-2 The integrated modeling framework of this study

2.4.2 Climate projections and meteorological downscaling

The climate projections are based upon the bias-corrected output of the National Center for Atmospheric Research's Community Earth System Model version 1 (CESM1) (Monaghan, A. J., Steinhoff, D. F., Bruyere, C. L., & Yates, 2014). We use the Weather Research and Forecasting (WRF) Model version 3.8.1 (Skamarock, W. C., Klemp, J. B., Dudhia, J., Gill, D. O., Barker, D. M., Duda, M. G., Huang, X.-Y., Wang, W., and Powers, 2008)to downscale the CESM1 output data from the original horizontal resolution of approximately 1° and a time interval of 6 h to a domain of 120×156 horizontal grid cells over the CONUS at a 36-km resolution and a time interval of 1 h. Downscaled meteorological fields are derived for the periods 2008–2012, 2028–2032, and

2048–2052 under both RCP4.5 and 8.5 climate scenarios. These meteorological fields are used to drive the BEIS and CMAQ-HDDM simulations.

The climate projections were based upon the bias-corrected output data from ensemble member #6 – also known as the "Mother of All Runs (MOAR)" – in the experiment of the National Center for Atmospheric Research's Community Earth System Model version 1 (CESM1) that participated in the Coupled Model Intercomparison Project Phase 5 (CMIP5). This dataset stemming from the output of ensemble member #6 has been bias-corrected using the European Centre for Medium-Range Weather Forecasts (ECMWF) Interim Reanalysis (ERA-Interim) fields for 1981-2005 and is widely used as initial and boundary conditions for meteorological downscaling of climate projections. We used the RCP4.5 and 8.5 climate projections from this dataset to conduct the meteorological downscaling, with the caveat that the projections can differ by the member of CESM1 simulations or by model. Nevertheless, ensemble member #6 is the only member containing 3-dimensional fields available at 6-hourly intervals necessary to force numerical weather prediction models for downscaling. Krayenhoff et al. indicated that the outputs from this particular member approximate the CMIP5 median in terms of projected summertime warming across the CONUS through the end of the 21st century.

The Weather Research and Forecasting (WRF) Model version 3.8.1 is used to downscale the CESM1 output data from an original horizontal resolution of approximately 1° and a time interval of 6 h to a domain of 120×156 horizontal grid cells at 36-km resolution and a time interval of 1 h. The modeling domain is centered at 40° N and 97° W and covers the entire CONUS and portions of southern Canada and northern Mexico. It contains 35 vertical levels, with the top level at 50 hPa. The model time step is set as 180 s. The physics options chosen in the WRF configuration include the Yonsei University scheme for planetary boundary layer dynamics, the Noah scheme for land surface model, the Rapid Radiative Transfer Model scheme for longwave radiation, the Dudhia scheme for shortwave radiation, a revised version of Kain-Fritsch scheme for cumulus parameterization, and the Lin et al. scheme for cloud microphysics. The CESM1 data are used as initial and boundary conditions and the meteorological nudging field in the WRF simulations. Spectral nudging was applied to temperature, horizontal winds, and geopotential heights, with a wave number of 3 in both zonal and meridional directions and a nudging coefficient of 3×10^{-4} s^{-1} for all the variables. Horizontal winds were nudged at all vertical levels. Other variables were nudged only at the levels above the planetary boundary layer. The nudging was conducted every 6 hours, consistent with the time interval of the CESM1 data. The same physics options and downscaling technique have been applied in previous studies showing good agreements with in situ observations and the high capacity to capture climate features in coarse-resolution climate projections from a global climate model.

Downscaling was conducted for the periods 2008–2012, 2028–2032, and 2048–2052 under both RCP4.5 and 8.5. To isolate the climate impacts, we kept the land cover pattern consistent between periods. WRF was restarted every six days, with the first 12 hours for spinning up. The downscaled fields were then processed by the Meteorology-Chemistry Interface Processor (MCIP) so that the outputs can be used directly to drive the biogenic model and CMAQ simulations. Our downscaled meteorological fields show average warming of 0.84 and 1.67 °C between 2010 and 2050 over the CONUS under RCP4.5 and 8.5, respectively. Figure S12 illustrates the spatial patterns of the 2-meter temperature changes under the two climate scenarios. It should be noted that the base year of the CESM1 climate projection is 2005, after which the climate conditions of different climate scenarios start to evolve by corresponding driving forces. Hence, the climate conditions in the period 2008–2012 differ between RCP4.5 and RCP8.5. However, the difference is relatively small (the mean difference in 2-m temperature between RCP4.5 and 8.5 over the CONUS are -0.04 °C), compared to the changes between 2010 and 2050 in a particular climate scenario. Therefore, we only used the 2010-period climate conditions under RCP4.5 to conduct the 2010-period simulations for biogenic emissions and air quality modeling. This ensured a consistent 2010 base case for the two climate scenarios in our study. Detailed information on the climate projections and meteorological downscaling procedure can be found in Figure S12.

2.4.3 Energy policy projects in the configurations of GT-NEMS

GT-NEMS is a computational general equilibrium (CGE) model based on the 2018 distribution of the United States Energy Information Administration (US EIA)'s National Energy Modeling System (NEMS), which generated US EIA's 2018 Annual Energy Outlook5. The Annual Energy Outlook forecasts energy supply and demand for the U.S. through 2050. Other than modifications necessary to operate the NEMS model on networked servers at Georgia Tech, GT-NEMS is equivalent to US EIA's NEMS.

Linear programming algorithms and other optimization techniques provide the foundation with which GT-NEMS develops forecasts of the US energy future. GT-NEMS uses twelve modules, plus a thirteenth integrating module, to simulate various sectors of the energy economy. These twelve sectors are each modeled by a respective module, and the corresponding twelve modules are Macroeconomic Activity, Residential Demand, Commercial Demand, Industrial Demand, Transportation Demand, Oil and Natural Gas Supply, Natural Gas Transmission and Distribution, Coal Market, Renewable Fuels, Liquid Fuels (formerly the Petroleum Market Module), International Energy, and Electricity Market. Figure S10 provides a graphical layout of the modular structure of GT-NEMS. GT-NEMS performs an iterative optimization process that results in the price and quantity that balance the demand and supply of numerous energy products. Regional differences in energy markets are reflected by the component modules of GT-NEMS that function at the regional level. The major region classifications include the 9 Census divisions for the end-use demand modules (Figure S1) and 22 regions/subregions of the North American Electric Reliability Corporation (NERC) for electricity (Figure S2). GT-NEMS generates regional and detailed results of the projections. These results are intended as forecasts of general trends rather than specific predictions of future outcomes, making GT-NEMS well-suited for offering insights about alternative policy and technology scenarios.

GT-NEMS models electric power systems through a regional planning approach that makes use of one module, the Electricity Market Module, and its four constituent sub-modules1. The Electricity Market Module divides the U.S. into 22 regions based on NERC regional boundaries. The Electricity Market Module performs separate projections of power demand and the cost-minimizing supply necessary to meet that demand for each region. To evaluate cost-minimizing supply choices, survey data on costs and performance of capacity types as well as end-use load shapes and other key variables are derived from US EIA's Forms 860, 861, and 923, Federal Energy Regulatory Commission's Form 1, and NERC projections6.

GT-NEMS models the demand sectors using nine Census Divisions. For buildings, appliances, industrial motors and drives, and combined heat and power (CHP) systems, NEMS adds or subtracts from the existing stock to account for new purchases, retrofits, and retirements. For mature technologies, timelines of equipment costs and efficiencies are specified by fuel type. For nascent technologies such as solid-state lighting and carbon capture, sequestration and utilization, endogenous learning curves model technology performance.

For residential buildings, GT-NEMS uses energy prices and macroeconomic indicators to estimate residential energy consumption for three building types (single-family, multi-family and mobile homes), 21 end-use services, and multiple fuel types. Logit functions assign market shares to competing technologies in ten major end-use services such as space heating, space cooling, and water heating. The implied discount rates are variable (ranging for space heating and cooling technologies from 15 to 42%). Price elasticity and rebound effects are applied to three of these end-uses (heating, cooling, and lighting) and are modeled separately for surviving equipment, replacement equipment, and new equipment using parameters that vary by equipment, housing type, and Census Division. Forecasts from commissioned reports are used for the 11 minor end-uses8. Based on projected building and appliance stocks, the energy integrity of the building envelope is then modeled.

In the commercial sector, GT-NEMS employs a least-cost function within a set of rules governing the options from which owners and operators of commercial buildings may choose technologies. GT-NEMS forecasts building stocks and the energy integrity of building envelopes before forecasting the stock of end-use technologies. GT-NEMS characterizes nearly 350 distinct types of end-use equipment and appliances in nine end-uses and eleven types of commercial buildings. Capital costs are amortized using “hurdle rates”, which are calculated for end-uses by year for different subsets of the population by summing the yield on U.S. government ten-year notes (endogenously determined) and the time preference premium of consumers (exogenous inputs to the model). Ninety percent of commercial floorspace is modeled using effective hurdle rates of 25% or more, and half employ discount rates ranging from 100% to 1000%. Three different decision types and three types of behavior rules are used depending on whether the technology would be a retrofit, replacement, or new addition, and if there is a change of fuel type. Thus, the model offers the potential for a rich examination of policy impacts and an assessment of technology choice, energy consumption, price and expenditures, carbon abatement, and pollution prevention over time and across Census divisions of the U.S.

Process energy in the industrial module is modeled separately for 16 manufacturing and 6 non-manufacturing industries by fuel type. The energy used per dollar of shipments (called unit energy consumption or UEC) is modeled for individual industries, based on energy use per ton of throughput at each process step. Future improvements in UEC are modeled by using Technology Possibility Curves (TPCs), which reflect UECs in the initial year, and annual energy intensity declines over time. The TPC rates are estimated separately for retrofitting of existing facilities and for construction of new facilities. The industrial module specifies cost and performance characteristics for a range of CHP and motor technologies.

GT-NEMS also provides projections of transportation energy demand by fuel type in the transportation sector, including motor gasoline, distillate, jet fuel, and alternative fuels such as ethanol and compressed and liquefied natural gas (CNG/LNG), based on a series of semi-independent submodules and components. The various modes of transport are considered, including private and fleet light-duty vehicles (LDVs); aircraft; marine, rail, and truck freight. Other transportation demands are also considered, such as mass transit, military, and recreational boating. This modular design allows for easy assessment of the impacts of policy initiatives, legislative mandates affecting individual modes of travel, and technological developments. In addition, the module provides projections of selected intermediate values necessary to determine energy consumption that is linked to projections of industrial output, international trade, and energy supply. These elements include estimates of passenger travel demand by light-duty vehicles, air, and mass transit; estimates of the energy requirements to meet this demand;

projections of vehicle stock and the penetration of new technologies; and estimates of the demand for truck, rail, marine, and air freight transport. The module consists of four submodules, including Light-Duty Vehicle (LDV), Air Travel, Freight Transport (heavy truck, rail, and marine), and Miscellaneous Energy Demand. The transportation module can evaluate a range of policy issues, including fuel taxes and subsidies; fuel economy performance by market class; fuel economy standards for light, medium, and heavy-duty vehicles; vehicle pricing by market class; demand for vehicle performance within market classes; fleet vehicle sales by technology type; alternative-fuel vehicle sales share; the California Low-Emission Vehicle Program; changes in vehicle-miles traveled (VMT); and various other policies and developments related to transportation energy use and greenhouse gas emissions.

Across these modules and regions, GT-NEMS projects the production, imports, conversion, consumption, and prices of energy, GDP, and employment subject to assumptions about macroeconomic and financial factors, world energy markets, resource availability and costs, behavioral and technological choice criteria, cost and performance characteristics of energy technologies, and demographics.

2.4.3.1 Baseline assumptions, EP scenarios, and emission projections

To project the future energy consumption, I started from a reference case using the same model inputs and assumptions as adopted by the 2018 version of the US EIA's NEMS used to generate the Reference case in the Annual Energy Outlook 2018 (AEO2018) The AEO2018 Reference case generally represents current legislation and environmental regulations, including implementing regulations, which were available as of the end of September 2017. The Reference case does not reflect the potential effects of proposed federal and state legislation, regulations, or standards, nor reflect the effects of sections of legislation that have been enacted but require funds and implementing regulations that have not been provided or specified. Data S1 summarizes the specific federal and state legislation and regulations represented in the Reference case. Based on the Reference case, we designed two EP scenarios, EP-CONT and EP-RELX, corresponding to continued and relaxed policies, respectively. Table S1 summarizes the differences in EPs implemented in these two scenarios. Detailed descriptions are provided in the following sections.

Extension/elimination of the Clean Power Plan (CPP). CPP was issued by US EPA to regulate CO_2 emissions from existing power plants under Section 111(d) of the Clean Air Act (Clean Air Act, 42 U.S.C. §§7401 et seq. (2013), §7411(d)). The CPP would require states to develop plans to meet specific targets by reducing carbon dioxide (CO_2) emissions from fossil-fired power plants13. States would be allowed to meet those targets through various means, including increasing the efficiency of fossil-fired plants, switching burning coal to natural gas, and substituting renewable energy for fossil fuels. To meet the targets, states would be allowed for regional cooperation through trading. The final aim of the CPP was to reduce CO_2 emissions from electrical power generation by 32% by 2030, relative to 2005 levels13. US EPA finalized the CPP in October 2015. However, the CPP was stayed by the U.S. Supreme Court in February 2016 and has never gone into effect. In August 2018, US EPA proposed the Affordable Clean Energy (ACE) rule as the replacement to the CPP, which was finalized in June 2019.

The AEO2018 Reference case didn’t include the CPP which was included in a side case (“Reference case with the Clean Power Plan”). EP-CONT assumed that the CPP would proceed as enacted, by following the assumptions and modeling of the CPP in the side case. The CPP rule sets interim and final CO_2 emissions performance rates for two subcategories of fossil-fired power unites: existing fossil steam unites with the interim/final rate of 1,534/1,305 lb CO_2/MWh net, and existing stationary combustion turbines with interim/final rate of 832/731 lb CO_2/MWh net. Interim rates must be met in 2022, and the final rate must be met in 2030. There is significant flexibility for states to implement the CPP which can be achieved based on either rate-based or mass-based state-specific standards. State-level cooperation is allowed. EP-CONT assumed that all region chose to meet a mass-based target and that trading was only allowed within NERC regions. EP-CONT further assumed an extension of the CPP beyond 2030 through 2050 by assuming the mass-based limits declining linearly to 50% reduction below 2005 levels with the same rate of decline in each state. Given that EP-RELX assumes no implementation of CPP, there is no difference in the model settings between EP-RELX and the Reference case with respect to the CPP rule.

Extension/early sunset of the production tax credit (PTC) and investment tax credit (ITC). The PTC is an inflation-adjusted per-kWh tax credit for electricity generated by eligible renewable energy resources or other technologies, including qualified geothermal electric, solar thermal electric, solar photovoltaics, wind, biomass, hydroelectric, municipal solid waste, landfill gas, tidal, wave, and ocean thermal. The duration of the credit is the first 10 years of operation for all facilities placed in service after August 8, 2005. The PTC was originally enacted in 1992 under the Energy Policy Act of 1992 (Freeman, 1992) and has been renewed and expanded numerous times, e.g., by the American Recovery and Reinvestment Act of 2009 (H.R. 1 Div. B, Section 1101 & 1102) in February 2009, the American Taxpayer Relief Act of 2012 (H.R. 8, Sec. 407) in January 2013, the Tax Increase Prevention Act of 2014 (H.R. 5771, Sec. 155) in December 2014, the Consolidated Appropriations Act, 2016 (H.R. 2029, Sec. 301) in December 2015, and the Bipartisan Budget Act of 2018 (H.R. 1892 Sec. 40409). The tax credit value is \$0.015 kWh-1 in

1993 dollars for some technologies and half of that for others. This tax credit value is adjusted for inflation by multiplying the original value by the inflation adjustment factor of the calendar year. In the AEO2018 Reference case, the tax credit value was \$0.024 kWh-1 in 2017 dollars for wind, poultry litter, geothermal, and closed-loop biomass, and \$0.012 kWh-1 in 2017 dollars for other renewable resources. As extended by the 2016 Consolidated Appropriation Act passed in December 2015, the tax credit is phased down for wind facilities and expires for other technologies commencing construction after December 31, 2016. The phase-down for wind facilities is as follows: 20% reduction in the PTC for facilities commencing construction in 2017; 40% reduction in the PTC for facilities commencing construction in 2018; 60% reduction in the PTC for facilities commencing construction in 2019. In EP-CONT, we assumed that the PTC for eligible generating technologies would retain its full value through 2050 as opposed to the phase-down for wind facilities and expiration for other technologies; In EP-RELX, we assumed that the PTC for all eligible technologies would expire in 2019.

The ITC for renewable generation technologies is a federal tax incentive for investment on individually-owned residential systems and business-owned systems. The ITC reduces the income tax paid by the person or company claiming the credit, based on a percentage of the amount invested in an eligible property. The ITC is primarily claimed by solar systems but also expanded to other renewable technologies otherwise eligible to receive the PTC. The ITC was originally established in the 1970s and amended through the Energy Policy Act of 2005 and a series of subsequent acts18-20. By reflecting the recent changes, the ITC in the AEO2018 Reference case is 30% for eligible facilities in electric power, commercial, and residential sectors commencing construction before December 31, 2019 and begins to phase down: the ITC for electric power and commercial sectors decreases to 26% in 2020 and 22% in 2021, and remains a permanent value of

10% in 2022 and after; the ITC for the residential sector is the same value as that for electric power and commercial sectors in 2020 and 2021 but phases out completely (0%) in 2022. In EP-CONT, we assumed that the ITC for electric power, commercial, and residential sectors remains its full value of 30% through 2050; in EP-RELX, we assumed that the ITC for all these sectors phases out completely in 2019.

The PTC and ITC are exclusive of one another. Following the AEO2018 Reference case, EP-CONT and EP-RELX assumed that the PTC is chosen for new geothermal plants and onshore wind projects whenever the PTC is available, and that the ITC is chosen for offshore wind farms because of their high capital costs.

New/no new efficiency requirements. The new/no new efficiency requirements focus on the joint Corporate Average Fuel Economy (CAFE) and Greenhouse Gas (GHG) Emissions standards for light-duty vehicles (LDVs) and efficiency standards for residential and commercial equipment. In October 15, 2012, the US EPA and the Department of Transportation's National Highway Traffic Safety Administration issued joint CAFE and GHG Emissions standards to further reduce GHG emissions and improve fuel economy for LDVs for model years (MYs) 2017 through 202521. The AEO2018 Reference case includes the joint emissions standards and assumes that the standards remain constant at MY 2025 levels in subsequent model years (Data S1). In EP-CONT, we assumed continued increase in joint CAFE and GHG emissions standards at an annual average rate of 0.4% after MY 2025 through the end of the projection; in EP-RELX, we assumed that the emissions standards would be held constant at MY 2021 levels in subsequent model years through 2050 with modest improvements in fuel economy because of economic, consumer, and other factors.

The AEO2018 Reference case reflects federal efficiency standards for residential and commercial equipment. The federal efficiency standards included in the Reference case must be currently in effect or finalized with compliance required at a future date, e.g., standards for general service incandescent light bulbs under the Energy Independence and Security Act of 2007; standards for residential torchiere lamps, dehumidifiers, and ceiling fan light kits under the Energy Policy Act of 2005; standards for commercial walk-in coolers, walk-in freezers, incandescent, and halogen lamps, metal halide lamp fixtures, and federal building lighting fixtures and bulbs under the Energy Independence and Security Act of 2007; standards for small commercial package air-conditioning and heating equipment, commercial refrigerators, freezers, refrigerator-freezers, automatic ice makers, ballasts for medium-base compact fluorescent lamps, low-voltage dry-type transformers, illuminated exit signs, traffic signals, and commercial premise spray valves under the Energy Policy Act of 2005, etc. Following an alternative policy case for new efficiency requirements in AEO2018, EP-CONT included additional updates to the federal efficiency standards for residential and commercial end-use equipment and a range of products that are not currently being covered, according to the timeline in the U.S. Department of Energy multiyear plan4; EP-RELX assumed the standards to be held constant at 2018 levels.

Emission estimation. The energy projections under EP-CONT and EP-RELX were translated into the projection of air pollutant emissions, comprised of 50 energy consumption sources (Table S2). For the electric power sector, we relied on GT-NEMS projection which provided the emission estimate only for this sector. GT-NEMS provided regional electric power emission estimates using a 22-region Electric Market Module mapping. The emissions were then reallocated into 9 Census Divisions to be consistent with other sectors, based on a conversion factor matrix that is essentially derived from historical sales data and coded in the GT-NEMS electricity load and demand submodule. For other sectors, we estimate the emissions using a bottom-up method: the emission was calculated as the energy consumption multiplied by corresponding emission factors (EF) (i.e., the mass of pollutant emitted per unit mass of energy consumed). In the transportation sector, the VMTs by vehicle type is projected by GT-NEMS with the EFs generated by the Motor Vehicle Emission Simulator (MOVES) version 2014b through 2050. EFs in residential, commercial, and industrial sectors were compiled based on the EPA's Air Pollutant Emissions Factors (AP-42) database and the EF database adopted in the PKU Inventory. Regional-level emission projections by 50 emission sources and 9 Census Divisions for the period 2017-2050 are thus generated. For air quality modeling purposes, we used a scaling method to harmonize the future projection of emissions with historical emission data and derive spatial-resolved future emission inventory. Since we used the USEPA's 2011 National Emission Inventory (2011) as the emission inventory for our historical CMAQ simulations (i.e., 2010 period), this emission inventory was the starting point for the scaling. The 2011 NEI was compiled on a 36-km spatial resolution, consistent with our CMAQ configuration. To obtain the scaling factors for 2011–2050, we used the state-level NEI emission data to determine the scaling factors for the period 2011–2017 and used our Census Division-level emission projections to determine the scaling factors for the period 2017–2050. 2017 is the joint year between historical emission data and our future projections. For the historical period, each state has specific scaling factors which further differ by sector (i.e., power, industrial, transportation, and residential/commercial) and pollutant. For the projection period, states within the same Census Divisions share the same scaling factors, which differ by sector, pollutant, and EP scenario. The emission inventory for future scenarios is generated by multiplying 2011 NEI data with corresponding scaling factors by state, sector, pollutant, and EP scenario (Figure S6). A comparison of the NOx emissions between our estimates and NEI for the year 2017 shows good agreement (Figure S11). Relative differences in emissions for individual sectors are within ±10% except for the residential/commercial sector, where our estimate is 26% higher than NEI, likely due to higher EFs we adopted from PKU inventory (Figure S11A). Spatially, our estimates resemble the regional pattern of NEI despite of some disparities found, for example, in West South Central and Pacific, where our estimates show higher emissions than NEI (Figure S11B).

2.4.3.2 Sensitivity analysis

While our study focuses on the impacts of EP relaxation on pollutants emissions, it is possible that certain fluctuations in economic growth, oil price, demographic trends, and other input assumptions could potentially modify the impacts of EP relaxation on emissions, inducing uncertainty in the energy projection and subsequently in emissions. Neither NEMS nor GT-NEMS provides uncertainty information on the energy projection. Therefore, instead of tracking the uncertainties directly in the model simulation, we conducted sensitivity simulations by changing the baseline assumptions and evaluated the impacts of EP relaxation on energy consumption and emissions in response to the assumption changes. Simulations for the two EP scenarios were conducted with baseline input assumptions for economic growth (real gross domestic product (GDP) grows at an average annual rate of 2.0% from 2017 through 2050), oil price (the Brent crude oil price rises to $144 per barrel in 2017 dollars by 2050), and demographic trends (resulting in moderate demand of resource). To examine the responses of outputs to fluctuations in various aspects of the input assumptions, six cases with different alternative input assumptions were tested. These cases are 1) the “high economic growth” case, which assumes real GDP growth at an average annual rate of 2.6%, 2) the “low economic growth” case, which assumes real GDP growth at an average annual rate of 1.5%, 3) the “high oil price” case, in which Brent spot price reaches

$299 per barrel in 2050, 4) the "low oil price" case, in which Brent spot price rises slowly to $52 per barrel in 2050, 5) the "high oil and gas resource and technology" case, which applies lower costs and higher resource availability of oil and gas than the baseline assumptions allowing for higher production of oil and gas at a lower price, and 6) the "low oil and gas resource and technology" case, which applied higher costs and lower resource availability of oil and gas. Further information about energy consumption with different sets of input assumptions can be obtained in US EIA's reports. Sensitivity simulations for EP-CONT and EP-RELX were conducted under these six sets of alternative input assumptions. The impacts of EP relaxation on NOx emissions under both the baseline assumptions and the alternative assumptions are summarized in Table S4. The results generally show consistent increases in air pollutant emissions due to EP relaxation under different economic and energy technology assumptions. As expected, NOx emissions in 2050 are greatest in the scenarios with high economic growth and low oil prices.

2.4.4 Biogenic emissions

I use the Biogenic Emission Inventory System (BEIS) version 3.61 (Bash et al., 2016) to evaluate biogenic emissions in 2010, 2030, and 2050. BEIS estimates the emissions of 33 BVOC compounds (i.e., isoprene, 14 monoterpene compounds, total sesquiterpenes, 16 other volatile organic compounds, and an aggregate group of other unspeciated volatile organic compounds), NOx, and carbon moNOxide (CO) (Bash et al., 2016). In this study, BEIS is modified to account for canopy-scale emission variations associated with LAI (Heald et al., 2009) and to incorporate the CO_2 inhibition effect on isoprene emissions (Heald et al., 2009). For consistency and equivalent comparison, the same WRF-downscaled meteorological fields used in CMAQ modeling are used to drive BEIS simulations.

The canopy model in BEIS accounts for the indirect impact of LAIs on leaf temperature. However, BEIS does not include dynamic schemes to account for the direct impact of LAIs on BVOC emissions, the indirect impact on photosynthetically active radiation (PAR) in the canopy, nor the CO_2 inhibition. The source codes were modified as follows to include relevant schemes based on the recommendation of previous studies. Guenther et al. recommended a parameterized canopy environment emission activity algorithm to account for canopy-scale emission variations associated with LAI. The relationship between emissions and LAI is estimated as,

$$\gamma_{\mathrm{LAI}} = \frac{0.49\mathrm{LAI}}{\sqrt{1+0.2\mathrm{LAI}^2}} \qquad (1)$$

where γ_{LAI} is an adjustment factor for emissions. Based on Equation (1), the direct and indirect impacts of the increase in LAI on emissions can be separated as follows,

$$\mathrm{R}_{\mathrm{LAI,direct}} = \frac{\mathrm{LAI}_{\mathrm{future}}}{\mathrm{LAI}_{\mathrm{current}}} \qquad (2)$$

$$\mathrm{R}_{\mathrm{LAI,indirect}} = \sqrt{\frac{1+0.2\mathrm{LAI}^2_{\mathrm{current}}}{1+0.2\mathrm{LAI}^2_{\mathrm{future}}}} \qquad (3)$$

where $\mathrm{LAI}_{\mathrm{current}}$ and $\mathrm{LAI}_{\mathrm{future}}$ denote the LAIs in the current and future periods, respectively; $\mathrm{R}_{\mathrm{LAI,direct}}$ is the ratio of future to current emissions due to the direct impact of LAI increase; and $\mathrm{R}_{\mathrm{LAI,indirect}}$ is the ratio of future to current emissions due to the indirect impact of LAI increase, including the impacts from both the LAI-induced changes in leaf temperature and PAR in the canopy. The absolute values of current LAIs were determined by the Moderate Resolution Imaging Spectroradiometer (MODIS) Leaf Area Index product, which is the default in WRF. The monthly LAI projections under RCP4.5 and RCP8.5 were derived from the CESM1 output in the RCP4.5

medium ensemble and RCP8.5 large ensemble experiments. Monthly gridded LAIs over the study domain are calculated as the ensemble means of multiple simulations and re-gridded to 36-km resolution over the study domain using linear interpolation. Based on the CESM1 LAI projections, we calculated the ratios of future to current LAI values. The spatial distributions of the relative changes in LAIs (the future-to-current ratios minus 1) between 2010 and 2050 were illustrated in Figure S4. These relative changes were applied to the MODIS-determined current LAI values to derive the absolute values of future LAIs. The BEIS source codes were modified to account for the direct and indirect impacts described by Equations (2) and (3). To avoid double-counting, the response of leaf temperature to future LAI change originally modeled in BEIS was excluded.

The CO_2 inhibition effect on isoprene emissions was incorporated in BEIS following the long-term response function in Heald et al.'s study[47]

$$\gamma_{C_\mathrm{a}} = I_{\mathrm{s,max}} - \left[\frac{I_{\mathrm{s,max}} \left(0.7C_\mathrm{a}\right)^h}{\left(C^*\right)^h + \left(0.7C_\mathrm{a}\right)^h} \right] \qquad (4)$$

where the values of the empirically-determined coefficients $I_{\mathrm{s,max}}$, C^*, and h are 1.344, 585, and 1.4614, respectively; C_a is the atmospheric CO_2 concentration in ppm. The CO_2 inhibition effect was only applied to isoprene emissions. The Biogenic Emissions Landuse Database version 4.1 for the year 2011 was used as the land use input. The WRF-downscaled meteorological fields were used to drive BEIS simulations. Ambient CO_2 concentrations were set constant in each period and scenario, with levels of 389, 435, and 486 ppm in 2010, 2030, and 2050 periods under RCP4.5 and of 389, 449, and 540 ppm in 2010, 2030, and 2050 periods under RCP8.5.

2.4.5 Air quality modeling

I use the CMAQ version 5.0.2 with HDDM to simulate O_3 concentrations and both the first- and second-order sensitivities of model species concentrations to NOx and VOCs emissions. We conduct 1) a five-year historical simulation using CMAQ driven by the 2008−2012 meteorological fields and the EPA's 2011 National Emission Inventory platform(US EPA, 2011b), 2) two five-year counterfactual simulations corresponding to the two EP scenarios, using CMAQ-HDDM driven by the 2008−2012 meteorological fields and the 2050 emission inventories, 3) four five-year future simulations corresponding to the two EP scenarios with the two climate scenarios, using CMAQ-HDDM driven by the 2048−2052 meteorological fields and the 2050 emission inventories, and 4) two one-year controlled simulations using CMAQ by changing the biogenic emissions and meteorological conditions, respectively, from 2010 to 2050 under EP-CONT and RCP8.5. Note that in addition to NOx, our simulations consider the EP relaxation-induced changes in anthropogenic emissions of all other major pollutants (SO_2, CO, NH_3, VOCs, and PM species) (see Table S3 for a summary of the changes in the total emissions of seven pollutants).

Based on the simulations, we calculate O_3 DVs by model grid cell. The DV of a given county is determined as the highest DV among all model grid cells intersecting any part of the county. We derive the future DVs by combining the modeled DVs with measurements(Centers for Disease Control and Prevention, 2019) using a relative response method (Foley et al., 2015). Based on the HDDM information, we derive isopleths of DVs for individual counties which are then converted to matrices containing only 0 and 1 values where 0 denotes attainment and 1 denotes nonattainment. The isopleth diagram of NNA as shown is generated by aggregating the 0/1 matrices of all counties together. The OPE is calculated using the first-order DDM information, while the first-order sensitivity of OPE is calculated using the first- and second-order DDM information.

The CMAQ version 5.0.2 with HDDM has been extensively evaluated in terms of photochemistry and widely used to simulate O_3 production. The horizontal grid resolution and the geographic projection of the modeling domain are the same as defined in WRF. The spatial coverage of the modeling domain (112×148) is slightly smaller than that in WRF (120×156), with 13 vertical layers extending to ~16 km above the ground. The EPA's NEI 2011 emission platform was used as the baseline emission inventory. The emissions were scaled up to 2050 by state and sector under both EP-CONT and EP-RELX based on the state-level emission projections mentioned above. The set of simulations conducted contains 1) a five-year historical simulation using CMAQ driven by the 2008−2012 meteorological fields and the EPA's NEI 2011 emission platform, 2) two five-year counterfactual simulations corresponding to the two EP scenarios, using CMAQ-HDDM driven by the 2008−2012 meteorological fields and the 2050 emission inventories, 3) four five-year future simulations corresponding to the two EP scenarios with the two climate scenarios, using CMAQ-HDDM driven by the 2048−2052 meteorological fields and the 2050 emission inventories, 4) two one-year controlled simulations using CMAQ by changing the biogenic emissions and meteorological conditions, respectively, from 2010 to 2050 under EP-CONT and RCP8.5. To minimize the influence of the initial conditions, each simulation started with a 10-day spin-up period.

CMAQ-HDDM calculates the semi-normalized first- and second-order sensitivities of both gas- and condensed-phase pollutants to precursors emissions. The sensitivity coefficients are expressed in the same units as concentrations as follows, thus allowing for easier interpretation and application:

$$S_{ij}^{(1)} = \frac{\partial C_i}{\partial \varepsilon_j} \qquad (5)$$

$$S_{ijk}^{(2)} = \frac{\partial^2 C_i}{\partial \varepsilon_j \partial \varepsilon_k} \qquad (6)$$

where $S_{ij}^{(1)}$ denotes first-order sensitivity of species i to parameter j; $S_{ijk}^{(2)}$ denotes second-order sensitivity of species i to parameters j and k; C_i denotes the ambient concentration of species i; ε_j and ε_k denote relative perturbations in parameters j and k. In this study, the two parameters of interest are the total anthropogenic NOx emissions and the total BVOC emissions. Five DDM parameters were defined accordingly, comprised of the first- and second-order sensitivities to anthropogenic NOx emissions, the first- and second-order sensitivities to BVOC emissions, and the second-order cross sensitivity to anthropogenic NOx emissions and BVOC emissions. These sensitivities are local and represent how concentrations respond to changes in precursor emissions in the nonlinear photochemical system. It should be noted that although HDDM is more efficient for calculating sensitivities than the traditional brute-force approach, it is still computationally expensive. The average CPU time to achieve a 1-day CMAQ-HDDM simulation with two first-order and three second-order sensitivity parameters is about 18 hours, though this could vary by hardware condition (the CPU we used is AMD Opteron(tm) Processor 6378, 2.4 GHz). The total CPU time of our simulation experiment is about 9,000 days.

2.4.5.1 Calculation of DVs

A DV is a statistic used by EPA to describe the air quality status of a given location relative to the NAAQS level and determine whether an area is subject to nonattainment. In this study, the DV in each of the five-year periods (i.e., 2008-2012 and 2048-2050 under RCP4.5 and RCP8.5) in a given grid cell was calculated as the five-year mean of the annual 4th highest MDA8h O_3. To be consistent with the EPA's data handling convention, the decimal digits of a DV in the unit of ppb were truncated. For example, an estimated DV of 70.875 ppb is recorded as 70 ppb and thus meets the current standard of 0.070 ppm. An area is designated as "nonattainment" if the DV is higher than the standard level. In EPA designations, the DV of a county is the highest one among monitoring sites. Note that about three-quarters of the US counties do not have an O_3 monitoring site measuring with the Federal Reference/Equivalent Method. To best reflect the CAA's requirement and EPA designations, the DV of a given county in this study was determined as the highest DV among all model grid cells intersecting any part of the county.

The modeled county-level DVs in this study were compared with county-level DVs from a dataset provided by the Centers for Disease Control and Prevention (CDC). The CDC dataset combines O_3 monitoring data from the EPA repository of ambient air quality data with simulated O_3 data. The dataset provides maximum, median, mean, and population-weighted MDA8h O_3 within each county covering all counties in the CONUS on a daily resolution spanning from 2001 to 2014. We used the dataset-recorded annual 4th highest MDA8h O_3, averaged over 2009-2013, in each county to compare with our historical five-year simulation for the 2010 period. The reason for using the 2009-2013 average values instead of 2008-2012 is that our historical simulation was driven by the 2011 NEI emission inventory. The 2009–2013 average values are expected to better approximate the O_3 concentrations at the 2011 emission level than the 2008-2012 average values. The results show good agreement between our simulation and the CDC data (Figure S13). Most of the differences fall within the range of (-10%, 10%). To further reduce the model bias, we derived county-specific relative response factors (RRFs) which are defined as the ratios of modeled future O_3 to modeled historical O_3. We then multiplied RRFs with CDC-recorded DVs to get the final DVs of future projections. This RRF method is recommended by EPA for modeled attainment test and has been shown to provide better estimates of future DVs than using the modeled predictions alone.

The multi-year simulations for individual periods allow us to address the variations in DVs and in the number of non-attainment counties (NNA) due to year-by-year climate anomalies. For each county, the standard deviation (SD) of the five-year mean of the DVs during a certain period was calculated as the SD of the five-year DVs divided by the square root of five. The 95% confidence interval was derived from the SD of the mean by assuming a normal distribution in DVs. Different from the DVs, NNA has a maximum, i.e., the total number of U.S. counties. We assumed that NNA can be treated as a percentage which follows the binomial distribution. We first divided NNAs by the total number of counties and then applied the angular transformation to the percentage values. The 95% confidence interval of NNA was determined on the angular-transformed scale, following the same procedure as the DVs on the normal scale, and then was inversely transformed to get the final uncertainty range.

2.4.5.2 Isopleths of DVs and NNA

Our CMAQ-HDDM simulations generated local first- and second-order sensitivities to NOx and BVOC emissions for four specific cases or four points (P1−4). P1 and P2 are EP-CONT and EP-RELX under the 2010 climate, respectively; P3 and P4 are EP-CONT and EP-RELX under the 2050 climate, respectively. In all the cases, the year for anthropogenic emissions is 2050. For each county, the HDDM information is derived from the model output for the day corresponding to the 4th highest MDA8h O_3 and averaged over five years. From each of the four points of P1-P4, county-level isopleth diagrams can be generated using a reduced form model (RFM) that is based on HDDM information, as follows,

$$C_{pre} = C_{base} + \Delta\varepsilon_{NO_X} \times S^{(1)}_{O_3,NO_X} + \Delta\varepsilon_{BVOC} \times S^{(1)}_{O_3,BVOC} + \frac{\Delta\varepsilon^2_{NO_X}}{2} \times S^{(2)}_{O_3,NO_X} + \frac{\Delta\varepsilon^2_{BVOC}}{2} \times S^{(2)}_{O_3,BVOC} + \Delta\varepsilon_{NO_X} \times \Delta\varepsilon_{BVOC} \times S^{(2)}_{O_3,NO_X,BVOC} \quad (7)$$

where C_{pre} is the predicted O_3 concentration with perturbed emissions of anthropogenic NOx and BVOCs; C_{base} is the modeled O_3 concentration with zero perturbations in emissions; $\Delta\varepsilon_{NOx}$ and $\Delta\varepsilon_{BVOC}$ are the fractional perturbations in emissions of anthropogenic NOx and BVOCs, respectively; $S_{O3,NOx}^{(1)}$ and $S_{O3,NOx}^{(2)}$ are the first- and second-order sensitivities of O_3 concentration to anthropogenic NOx emissions; $S_{O3,BVOC}^{(1)}$ and $S_{O3,BVOC}^{(2)}$ are the first- and second-order sensitivities of O_3 concentration to BVOC emissions; $S_{O3,NOx,BVOC}^{(2)}$ is the second-order cross sensitivity of O_3 concentration to anthropogenic NOx and BVOC emissions. We then combine the four isopleth diagrams generated individually by P1-P4 using a stepwise-based HDDM method with the Gaussian function as the weighting function. This approach ensures that the isopleth diagrams are constrained by the four points simultaneously, and isopleths in the area closer to a certain point are to a larger extent regulated by the first- and second-order sensitivities of that point. The scale of the isopleth diagrams along the BVOC direction was adjusted to a yearly time scale using a cubic curve which described the BVOC emission changes over time and is determined by the levels of the BVOC emissions in the three periods of 2010, 2030, and 2050. This procedure transforms the isopleth diagrams from the NOx-BVOC coordinate to the NOx-Year coordinate. The matrix of the isopleth diagram of DVs for each county is then converted to a matrix containing only 0 and 1 where 0 denoted attainment and 1 denoted nonattainment. The isopleth diagram of NNA is generated by aggregating the 0/1 matrices of all counties together.

The isopleth diagrams were extended based on the HDDM information to diagnose the impacts of larger changes in NOx emissions on O_3 than the range (i.e., -2% ~ 8%). Using the extended isopleth diagrams, we estimated the yearly trend of NNA_{60} during the period 2010–2050 and found that under EP-RELX and RCP8.5, the NNA_{60} in 2050 (879) will roll back to the level in between 2021 (915) and 2022 (863). We also evaluated the NNA_{60} under different assumptions of the energy projection using the extended isopleth diagrams (Figure S9). Note that our CMAQ-HDDM simulations, which provide information on local sensitivities, were conducted for P1–4 exclusively. While the NNA values at P1–4 under baseline assumptions were explicitly modeled, the NNA values in the sensitivity tests were approximated using the RFMs obtained from the HDDM information and may deviate from model simulation results due to the local feature of the sensitivities. CMAQ simulations are recommended to explicitly diagnose the NNA changes in response to further decrease or increase in NOx emissions under other specific scenarios.

To monetize the cost of the increase in NNA_{60} due to EP relaxation and climate change, we estimated the amount of emission reduction that could offset the NNA_{60} increase. A similar RFM was established based on the HDDM information derived from the 2050 EP-RELX simulations. The emission reduction was determined by reducing NOx emissions to the NNA_{60} level as P1 in Figure 4B. This amount of NOx reduction was then monetized by adopting the estimates of the average annualized NOx offset prices from a previous study, which range from $3,700 (in 2011$) for known controls to $16,000 for unknown controls. We used these two prices to bound our estimation. The lower bound of our cost estimates assumes that all emission reductions come from known controls, whereas the higher bound of our estimates assumes all emission reductions from unknown controls.

2.4.5.3 DDM-based calculation of OPE

OPE has historically been a popular indicator to measure the relationship between O_3 and NOx. OPE is defined as the number of molecules of O_3 produced per each molecule of NOx removed from the photochemical cycling between NO and NO_2. Since each NOx molecule entering the system must leave, the emission rate approximates the loss rate across a large spatial scale. OPE has important policy implications since it provides an estimate for how much more (or less) O_3 would be formed from an incremental increase (or decrease) in NOx emissions. The reaction of NO_2 with OH, which forms nitric acid, is typically the dominant pathway for NOx loss. In this study, OPE was calculated using the first-order DDM information, while the first-order sensitivity of OPE was calculated using the first- and second-order DDM information. The equation to calculate OPE is as follows,

$$OPE = \frac{S^{(1)}_{O_3,NO_X} + S^{(1)}_{NO_2,NO_X}}{S^{(1)}_{NO_Z,NO_X}} \quad (8)$$

where $S_{NOz,NOx}{}^{(1)}$ is the sum of the first-order sensitivities of all NO_Z compounds (peroxyacetyl nitrate, peroxynitric acid, organic nitrate, nitric acid, nitrous acid, nitrate radical, aerosol nitrate, and dinitrogen pentoxide) to anthropogenic NOx emissions. Based on Equation (8) and using the quotient rule for derivatives, the first-order sensitivity of OPE to anthropogenic NOx emissions was calculated as,

$$S^{(1)}_{OPE,NO_X} = \frac{S^{(2)}_{O_3,NO_X} \times S^{(1)}_{NO_Z,NO_X} + S^{(2)}_{NO_2,NO_X} \times S^{(1)}_{NO_Z,NO_X} - S^{(1)}_{O_3,NO_X} \times S^{(2)}_{NO_Z,NO_X} - S^{(1)}_{NO_2,NO_X} \times S^{(2)}_{NO_Z,NO_X}}{S^{(1)}_{NO_Z,NO_X} \times S^{(1)}_{NO_Z,NO_X}} \quad (9)$$

where $S_{NOz,NOx}^{(2)}$ is the sum of the second-order sensitivities of all NO_Z compounds to anthropogenic NOx emissions.

2.4.6 Estimating the monetized impacts from ozone concentrations

The health impacts are estimated according to the framework developed for Environmental Benefits Mapping and Analysis Program (BenMap) by US EPA (US EPA, 2018). This framework, presented in Figure 2-3, starts from the ozone projected design values (DV), which in this chapter are calculated. Population estimates up to 2050 and baseline incidence (mortality) rates are simulated using EPA's tool Population Simulation Model, PopSim. The next step is inserting these three sets of inputs into the preselected health impact function, from which health effect can be projected in terms of change (delta) in mortality incidence at the county level for each year. Finally, adopting the value for statistical life that EPA summarized monetizes the health impacts into quantified benefits and costs estimates in terms of U.S. dollars. The supplemental materials, the Supplemental Experimental Procedures, will explain more details for each procedure.

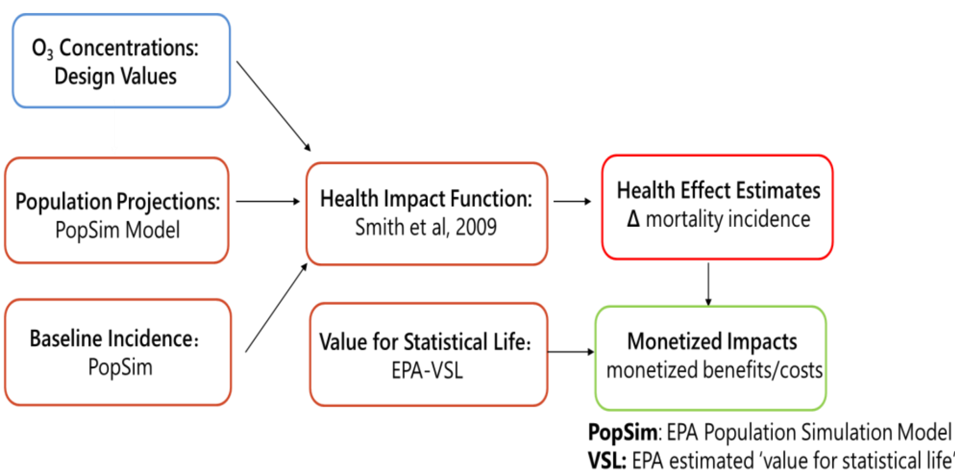


Figure 2-3 The framework to monetize the environmental impacts

2.5 Results

2.5.1 The EP impact on NOx emissions

We investigate two EP scenarios of 1) continued (EP-CONT) and 2) relaxed (EP-RELX) policies (Table S1). EP-CONT (the baseline scenario) assumes consistent implementation of U.S. laws, regulations, and international protocols that were in place as of the end of September 2017. This scenario additionally assumes the enforcement and extension of the existing CPP, the extension of the Production Tax Credit (PTC) and the full Investment Tax Credit (ITC) for renewable energy, and continued stringent federal efficiency standards in the transportation, residential, and commercial sectors. EP-RELX is based on EP-CONT but excludes the effects of CPP, assumes early sunsets of PTC and ITC, freezes the light-duty vehicle standards at 2021 levels, and assumes no new federal efficiency standards (Table S1). A bottom-up method is applied in the translation of the GT-NEMS energy projections to emissions of seven air pollutants from 50 emission sources (Tables S2 and S3). Note that our projections do not consider any proposed or presently nonexistent air pollutant emission standards and therefore should represent the higher bound of the future trends in air pollutant emissions. Projections include baseline assumptions for economic growth, oil price, and resource availability. We also conduct sensitivity simulations by introducing alternative assumptions, such as high and low economic growth, to test the robustness of these projections. EP relaxation affects the emissions of many air pollutants, which are included in the assessment (Table S3). Our discussion here focuses on NOx emissions.

Similar to previous reports conducted by US EPA, for example (US EPA, 2011a), under the assumption of baseline economic growth, our projections initially show continuously decreasing total NOx emissions (the solid black line in Figure 2-4A), though we find the trend flattening gradually after 2030 and reaching a minimum around 2040 (Figure 2-4A). The flattening trend after 2030 is the competing result of the increase in energy consumption coupled with the decrease in emission factors (EF, the mass of a pollutant emitted per unit mass of energy consumed). Our projection accounts for the impacts of air pollutant emission standards only for the standards that are currently finalized. Given that for all sectors, most of the finalized standards driving the decrease in EFs would come into effect before 2030, an absence of new-standard phase-ins would lead to a modest decrease in EFs after 2030, which would be gradually offset by the growing energy consumption during the same period. As a result, there is a slight increase in the NOx emissions between 2040 and 2050, with an average annual rate of +0.2% under baseline economic growth. This increase is sharper under high economic growth, while there is no such increase under low economic growth (Figure 2-4A), reflecting the importance of economic development for NOx emissions.

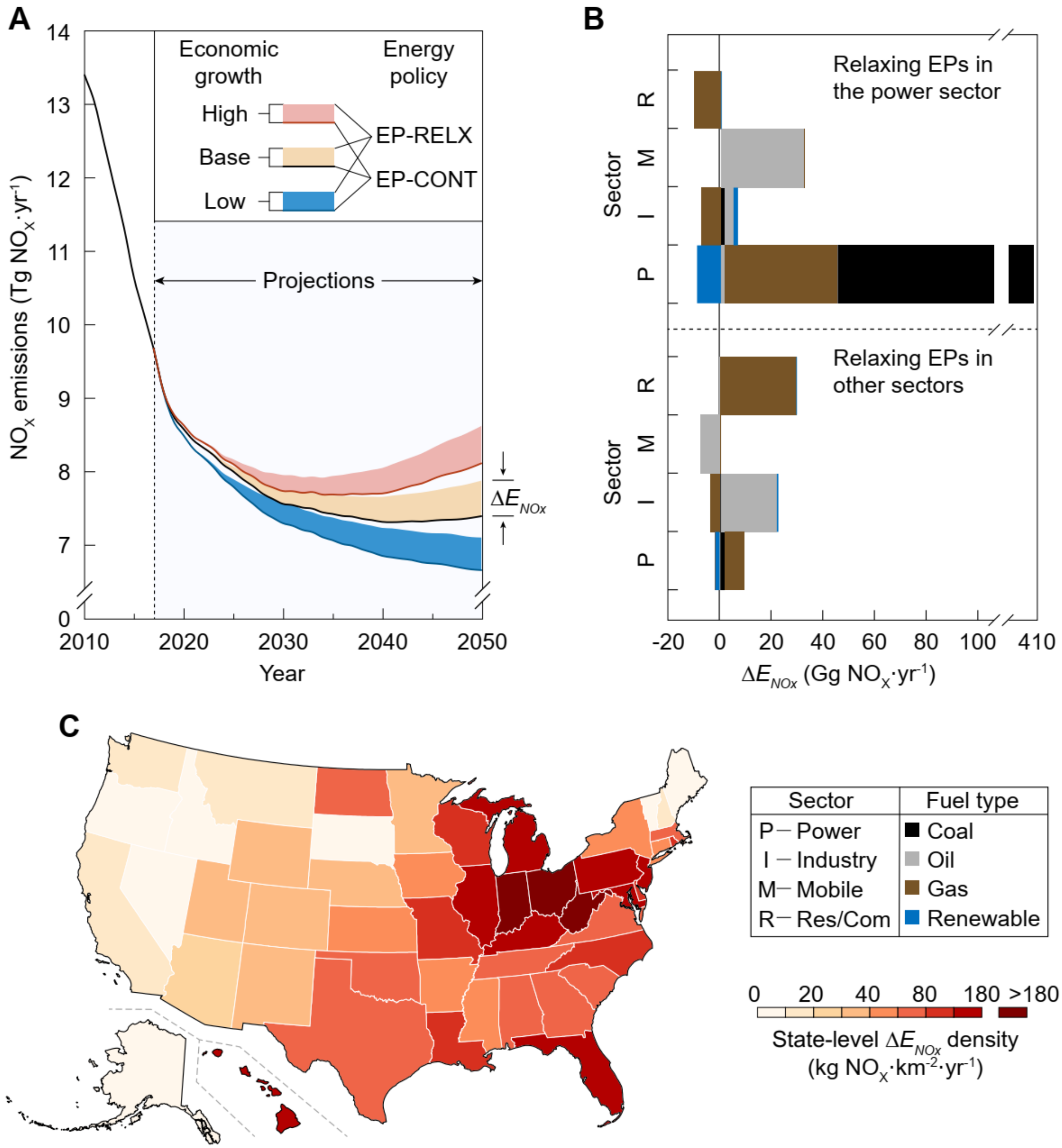


Figure 2-4 Projected increases in anthropogenic NOx emissions in the United States due to EP relaxation

(A) Projected trends in NOx emissions under different economic scenarios showing an increase in NOx emissions due to relaxation of EPs. (B) Attribution of ΔE_{NOx} *to EPs, sectors, and fuel types in 2050. EPs are divided into two groups:*

*CPP- and PTC/ITC-related EPs which mainly target the power sector; and EPs related to efficiency requirements targeting other sectors (i.e., residential, commercial, and transportation). The impacts of relaxing these two groups of EPs on NOx emissions are separated and further decomposed into four sectors and four fuel types. (**C)** State-level* ΔE_{NOx} *densities in 2050.*

Under baseline economic growth, the EP relaxation increases the total anthropogenic NOx emissions by 480 Gg·yr-1 (or 6.5%) in 2050, compared to EP-CONT (Figure 2-4A and Table S3). Among all sectors, the power sector shows the highest emission increase (ΔE_{NOx})—416 Gg·yr-1 (or 64%)—due to the EP relaxation, primarily as a result of increased coal use for electricity generation (Figure 2-4B). Further investigation reveals that both EP scenarios show nearly zero additions of coal-fired electricity capacity during the projection period and that most of the increased coal use in the EP-RELX scenario is from the retention of existing plants that would otherwise be retired under the EP-CONT scenario. The relaxation of EPs increases NOx emissions regardless of the varied assumptions for economic growth, oil price, and resource availability (Figure 2-4A and Table S4). The total ΔE_{NOx} from all sectors varies moderately by assumption, ranging from 340 Gg·yr-1 under the assumption of high oil and gas availability to 530 Gg·yr-1 under the assumption of high economic growth (Table S4). The disparity in ΔENOx implies that EP relaxation intervenes with model assumptions for socioeconomic drivers (i.e., economic growth, oil price, and technology), which contributes to the uncertainties in future projections of energy and emissions in response to EP relaxation. However, the ΔE_{NOx} values are consistent in sign regardless of the variations in these socioeconomic drivers, and the standard deviation of the ΔE_{NOx} values across the sensitivity tests (62 Gg·yr-1) is relatively small compared to the ΔE_{NOx} mean (445 Gg·yr-1). Thus, we adopt our analysis based on the scenario with baseline assumptions, being reasonably representative of the effects of EP relaxation under other scenarios. Key results are highlighted for three sectors below:

• With the baseline assumptions, a decomposition analysis of fuel type shows an increased contribution of coal consumption (381 $Gg\cdot yr^{-1}$) to NOx emissions under EP-RELX, compared to EP-CONT, due mainly to the elimination of CPP and the early sunsets of PTC and ITC, the combination of which increases coal consumption in the power sector by 3.5 $EJ\cdot yr^{-1}$ by 2050 (approximately one third of the total coal consumption) and further impacts other sectors and fuel types (Figure 2-2B).

• Residential emissions from gas combustion increase by 30 $Gg\cdot yr^{-1}$ due to the elimination of the fuel efficiency requirements.

• Air pollutant emissions from on-road vehicles are relatively insensitive to fuel efficiency standards (Figure 2-4B) due to on-road standards for CO, VOC, and NOx emissions (e.g., Tier-3 Motor Vehicle Emission and Fuel Standards(US EPA, 2014a)) that are separate from CAFE. Our analysis suggests that the total vehicle miles traveled for light-duty vehicles (LDVs) would increase by 1.2% with more stringent fuel efficiency requirements, resulting from a rebound in travel due to lower fuel costs (Sorrell & Dimitropoulos, 2008). As a result, a relaxation of EPs leads to a slight decrease in on-road LDV emissions (7.4 $Gg\cdot yr^{-1}$ or 0.34% of the total NOx) in 2050, in line with previous estimates (Control of Air Pollution From Motor Vehicles: Tier 3 Motor Vehicle Emission and Fuel Standards, 2014).

Our assessment projects energy and emissions for each of the nine U.S. Census Divisions (See Figure S1 for details). Based on the future-to-current ratios of the projected emissions and the 2011 National Emission Inventory (US EPA, 2011b), we derive spatially resolved emissions in 2050 by pollutant, source, region, and scenario at a 36-km spatial resolution, which are used as inputs in air quality modeling. Spatially, EP relaxation leads to higher increases in NOx emissions over the eastern regions than the western regions (Figure 2-4C), due mainly to the greater total electricity demand and higher dependence on coal-fired generation in the eastern U.S. The shift in the energy mix and the increase in NOx emissions are most pronounced in the Great Lakes region (Figure 2-4C and Figure S2) where EP relaxation increases coal use for electricity generation by 290% and increases NOx emissions from the power sector by 88%. In contrast, coal-fired generation in California is projected to end by 2023 under both EP scenarios due to other strict emission laws and aggressive energy goals for the state (California Global Warming Solutions Act of 2006: Emissions Limit, 2016), resulting in minor effects of EP relaxation on the local energy mix and NOx emissions (Figure 2-4C).

2.5.2 Projection of biogenic emissions under climate change

I estimated BVOC emissions over the CONUS for 2008–2012, 2028–2032, and 2048–2052 (Experimental Procedures and Supplemental Experimental Procedures). The developed BVOC emission inventories are subsequently input into the CMAQ model to simulate O_3 concentrations under different scenarios to investigate the impacts of EP relaxation and climate change on ambient O_3 concentrations. The results and discussion presented in the following sections focus on the simulations under the Representative Concentration Pathway (RCP) 8.5 (a climate scenario with an intensive increase in temperature) but also include simulations under RCP4.5 (a scenario with a moderate increase in temperature) for comparison. The most important finding regarding BVOC emissions is continuously increasing emissions of BVOCs over the period 2010–2050 (Figure 2-5 and Figure S3), particularly under RCP8.5 (+19.0% between 2010 and 2050) compared to RCP4.5 (+13.0%). This finding is expected due primarily to the changing environmental conditions (temperature, solar radiation, etc.) as simulated in future scenarios. The increasing BVOC emissions are expected to impact the concentrations of O_3 pollution, considering their important role in tropospheric O_3 chemistry (Atkinson & Arey, 2003). The analysis of the intra-annual profile of the BVOC emission changes reveals high emission growth during summertime (June-July-August) (Figure 2-5A). Significant increases are also evident in spring (March-April-May) (Figure 2-3A) mainly due to large increases in LAIs during this season projected by CESM1 (Figure S4, Experimental Procedures), likely as a result of canopy emergence earlier in the year due to climate warming (Groffman et al., 2012; Walther et al., 2002). Spatially, the increase is more widespread under RCP8.5 than RCP4.5, with southern regions consistently showing higher increases than northern regions under both scenarios (Figure 2-5B). A decomposition analysis finds that the meteorological changes (excluding the impacts of the changes in LAIs and CO_2) lead to an increase of 6.6 $Tg \cdot yr^{-1}$ in the total emission of 33 BVOC compounds under RCP8.5 (see Experimental Procedures for speciation), which is 94% higher than the increase under RCP4.5 (Figure S5). However, the overall difference between RCP4.5 and RCP8.5 is reduced when considering inhibition of the leaf-isoprene metabolism due to increases in atmospheric CO_2(Wilkinson et al., 2009) and limits on LAI increases due to soil moisture stress in response to climate change. Compared to RCP4.5, higher CO_2 concentrations and less LAI increases under RCP8.5 are projected to moderate emission changes.

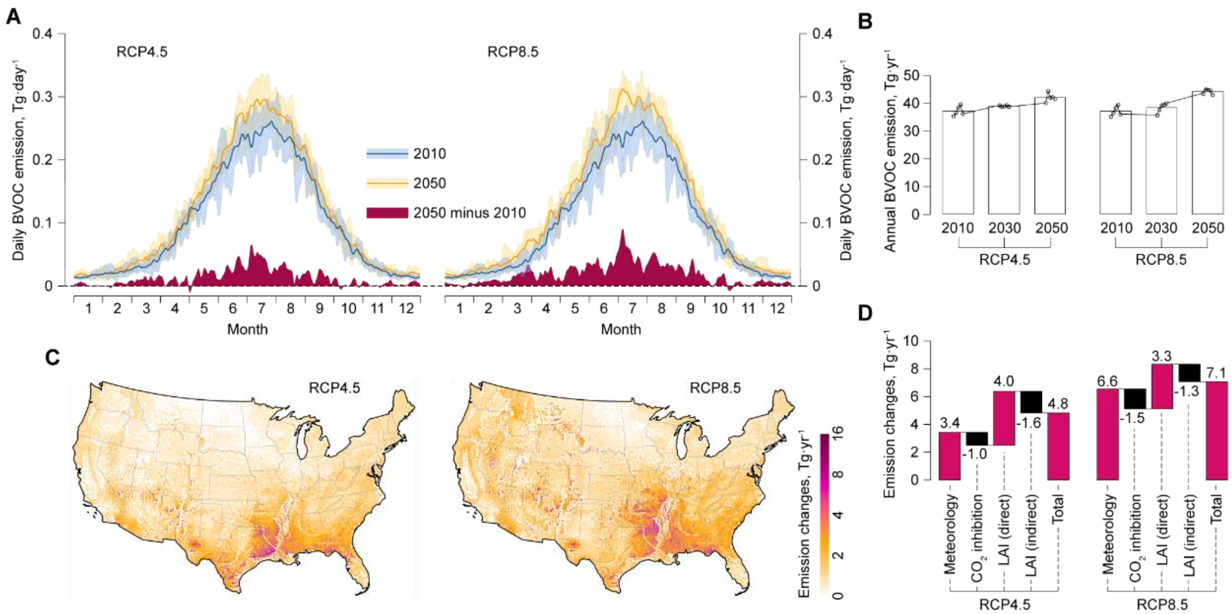


Figure 2-5 Projections of future changes in BVOC emissions under RCP4.5 and RCP8.5 climate scenarios

BVOC emissions in 2010, 2030, and 2050 are estimated by considering the differences in meteorology, atmospheric CO_2 concentrations, and LAIs between different periods. For each period, the results are calculated as five-year means (e.g., 2008–2012 for the period 2010). (A) Temporal trends of daily BVOC emissions (three-day running means) over the CONUS in 2010 and 2050 under RCP4.5 and RCP8.5. Bold solid lines show the five-year average in each period (2010/2050). Shaded areas around the lines show the variation in the estimates of individual years. The red areas represent the temporal trends of the differences in emissions between 2050 and 2010 (2050 minus 2010). (B) Annual total BVOC emissions in 2010, 2030, and 2050 under RCP4.5 and RCP8.5. Five-year means are shown as boxes; individual years are shown as circles. (C) Spatial changes in BVOC emissions under the two climate scenarios between 2010 and 2050. (D) Attribution of changes in BVOC emissions to individual driving factors between 2010 and 2050.

2.5.3 *Effects on ground-level O_3 by county*

Based on the projections of anthropogenic emissions, meteorology, and BVOC emissions, I conducted an ensemble of CMAQ-HDDM simulations to evaluate the responses of ground-level O_3 to EP relaxation and climate change (Experimental Procedures). EP relaxation increases anthropogenic emissions, and climate change modifies meteorology and increases BVOC emissions. For each county of the CONUS, the effects of these changes on O_3 are summarized in an isopleth diagram with the extent of EP relaxation (represented by ΔE_{NOx}) as one independent variable and the extent of climate change (represented by specific years) as the other, with the O_3 design value (DV, the fourth-highest MDA8h O_3)(US EPA, 2014b) as the dependent variable forming the isopleths (Experimental Procedures and Supplemental Experimental Procedures). Figure 2-6 illustrates the isopleths for three representative counties under RCP8.5. In Los Angeles County (Figure 2-6A), the projected DVs in 2050 under RCP8.5 greatly exceed the current standard level of 0.070 ppm. In New York County (Figure 2-6B), the projected DVs are slightly below the 0.070 ppm-level. In Fulton County (Atlanta) (Figure 2-6C), the DVs fall between the 0.060- and 0.065-ppm levels. The DVs are more sensitive to climate change than to the relaxation of EPs in Los Angeles County and New York County, where local NOx emissions are relatively high, while the opposite is evident in Atlanta because this metropolitan area is enriched in BVOCs due to high forest coverage. Correlation analysis shows a significant positive correlation between the log-transformed county-level population densities of all counties of the CONUS and their DVs' sensitivities to climate change (r = 0.17; significance level = 0.01; P << 0.0001), suggesting that in terms of O_3 pollution, the effect of climate change is greater in densely populated areas than in sparsely populated areas. The different DV responses to EP relaxation and climate change can largely be explained by the different features between the NOx- and VOC-sensitive regimes of O_3

chemistry, but the spatial heterogeneities of ΔE_{NOx} driven by EP relaxation and the changes in meteorology and BVOC emissions driven by climate change make counties further differ in the isopleth patterns.

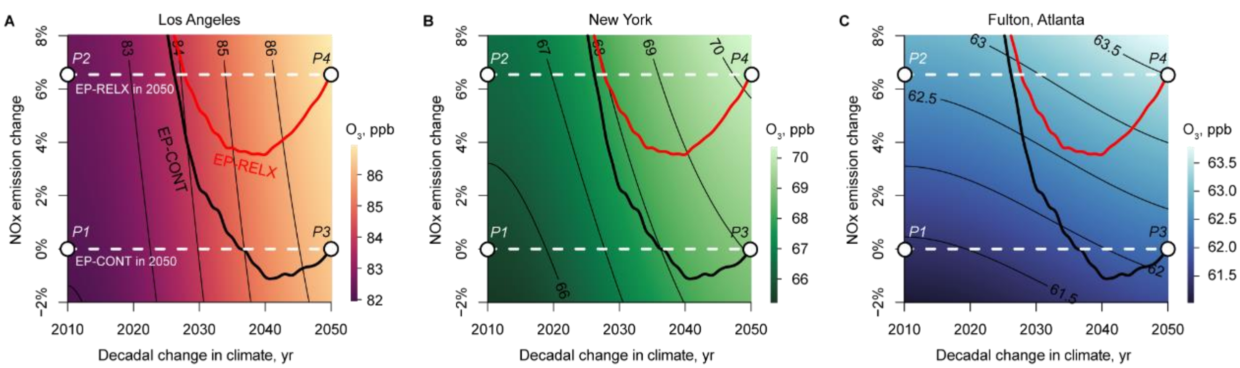


Figure 2-6 Projections of DVs in response to EP relaxation and climate change under RCP8.5

in (A) Los Angeles County, (B) New York County, and (C) Fulton County, Atlanta. Isopleth diagrams are calculated using HDDM applied to a group of five-year simulations (See Methodology for details). The extent of climate change is characterized by specific years, assuming a general temporal trend in climate change. Sensitivities derived from HDDM are averaged over each five-year period so that the interannual meteorological variability is smoothed. The pathways linking climate change to ground-level O_3 consist of both the changes in meteorology and BVOC emissions. EP relaxation is denoted by the NOx emission change which is calculated by the percentage change relative to the 2050 level in the EP-CONT scenario. Projected trajectories describing the simultaneous changes in NOx emissions and climate are marked on the isopleth maps as solid black (for EP-CONT) and red (for EP-RELX) lines. "P3" (EP-CONT) and "P4" (EP-RELX) show the trajectory endpoints of anthropogenic NOx emissions and climate for both policy scenarios in 2050. "P1" and "P2" show projected NOx emissions in 2050 with climate in 2010. The difference in DVs between P1 and P3 (between P2 and P4) reflects the impact of climate change on DVs by 2050 under EP-CONT (EP-RELX). The difference between P1 and P2 (between P3 and P4) reflects the impact of EP relaxation on DVs by 2050 without (with) consideration of climate change.

2.5.4 Nationwide effects on O_3-standard attainability

For an overall perspective of the nationwide impacts of EP relaxation and climate change on O_3-standard attainability, county-specific isopleth maps are aggregated to derive the isopleth map for the number of nonattainment counties (NNA) (Figure 2-7) (See Experimental Procedures and Supplemental Experimental Procedures for details). NNA_{70} is referred to as the NNA exceeding the 0.070-ppm standard; NNA_{60} is defined accordingly. Our historical simulations constrained by observations find an NNA_{70} of 851 out of the total 3109 counties within the CONUS in 2010 (Table S5). The NNA_{70} decreases to 27 (24–31, 95% confidence interval of the five-year mean) in 2050 with further reduced anthropogenic emissions as projected in the EP-CONT scenario under a stationary climate (i.e., P1 in Figure 2-7A and C). This reduction in NNA_{70} suggests that substantial health benefits will accrue from continuous ongoing emission reductions. Under the same conditions of P1, the NNA_{60} is 497 (445–551) (Figure 2-7B). Relaxing EPs (P1→P2) lead to an increase of 3 (2–4) in NNA_{70} (Figure 2-7A and C, Table S5). Climate change (P1→P3) under RCP4.5 and RCP8.5 leads to increases of 5 (0–11) and 10 (5–15) in NNA_{70}, respectively (Figure 2-7A and C, Table S5). We find that relaxing EPs while simultaneously considering climate change (P1→P4) leads to increases of 17 (9–26) and 22 (16–28) in NNA_{70} under RCP4.5 and RCP8.5, respectively (Figure 2-7A and C, Table S5), which are 112% (under RCP4.5) and 69% (under RCP8.5) greater than the increases by aggregating their individual effects, suggesting a synergistic effect on NNA_{70} between EP relaxation and climate change.

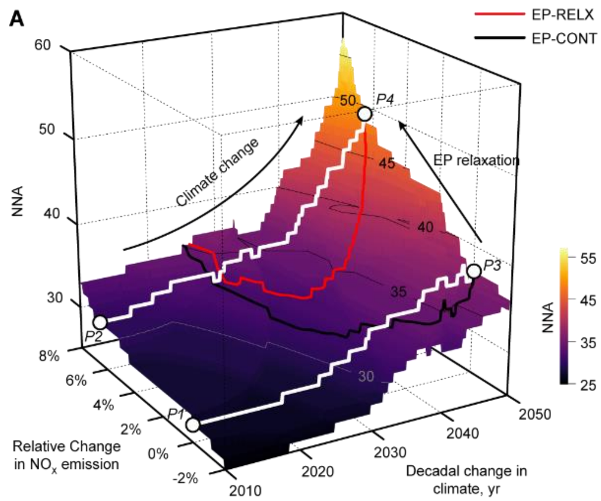


Figure 2-7 The synergistic effects of relaxation of EPs and climate change on NNA70 (A) and NAA60 (B).

Under the climate scenario RCP8.5, descriptions of the isopleths are detailed, explained in the caption of Figure 2-7. Given that NNA_{70} only involves a limited number of nonattainment counties, we focus further analysis on NNA_{60}, which brings more counties into consideration for nonattainment. The isopleths of NNA_{60} (Figure 2-7B and D) are smoother than those of NNA_{70} (Figure 2-7A and C). Consistent with NNA_{70}, a synergistic effect on NNA_{60} is evident. Relaxing EPs leads to an increase of 513 (136–171) in NNA_{60}; climate change under RCP4.5 and RCP8.5 leads to increases of 67 (31–104) and 143 (83–187) in NNA_{60}, respectively. Combining these two factors results in increases of 242 (198–287) and 382 (323–443) in NNA_{60} under RCP4.5 and RCP8.5, respectively, which are 10% (RCP4.5) and 33% (RCP8.5) greater than the increases by aggregating their individual effects. Under RCP8.5, a relaxation of EPs together with climate change (Figure 2-7D, P1→P4) would increase the NNA_{60} and NNA_{70} by 77%, from 497 to 879, and 81%, from 27 to 49, respectively, compared to the NNA values with neither EP relaxation nor climate change. Under RCP8.5, 35 of the lower 48 states would experience increases in NNA_{60}, with Illinois (an increase of 52 in NNA_{60}), Texas (40), Missouri (39), and Michigan (37) showing the largest increases (Figure 2-8). Note that our future projections of energy and emissions are conducted on a regional level. While we use scaling factors to spatially downscale the regional changes into the 36-km model resolution grid, the variation in the scaling factors inside a region is not considered (Figure S6). Therefore, our method captures the regional pattern of the changes in NNA in response to EP relaxation, but the changes in the attainment status for individual counties should be interpreted with caution. Fully offsetting the elevated O_3 levels over the CONUS caused by EP relaxation and climate change under RCP8.5 would require an additional reduction of 700 $Gg \cdot yr^{-1}$ in NOx emissions, which corresponds to an emission abatement cost at ~\$2.6–11.3 $billion \cdot yr^{-1}$ (in 2011\$).

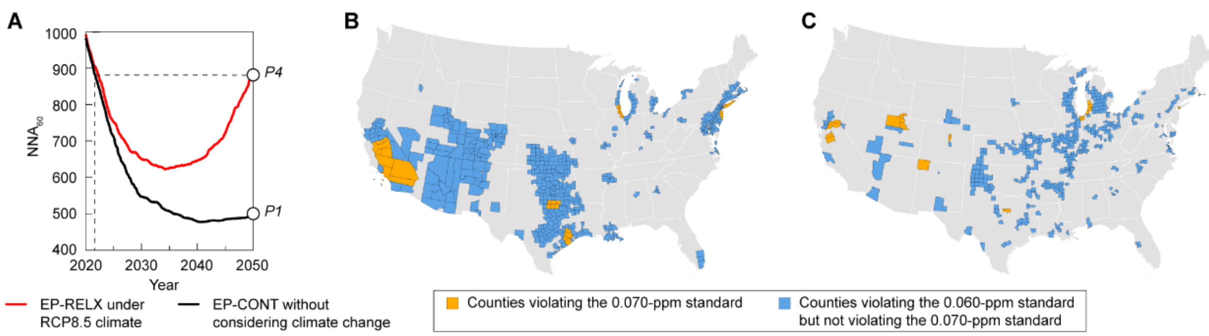


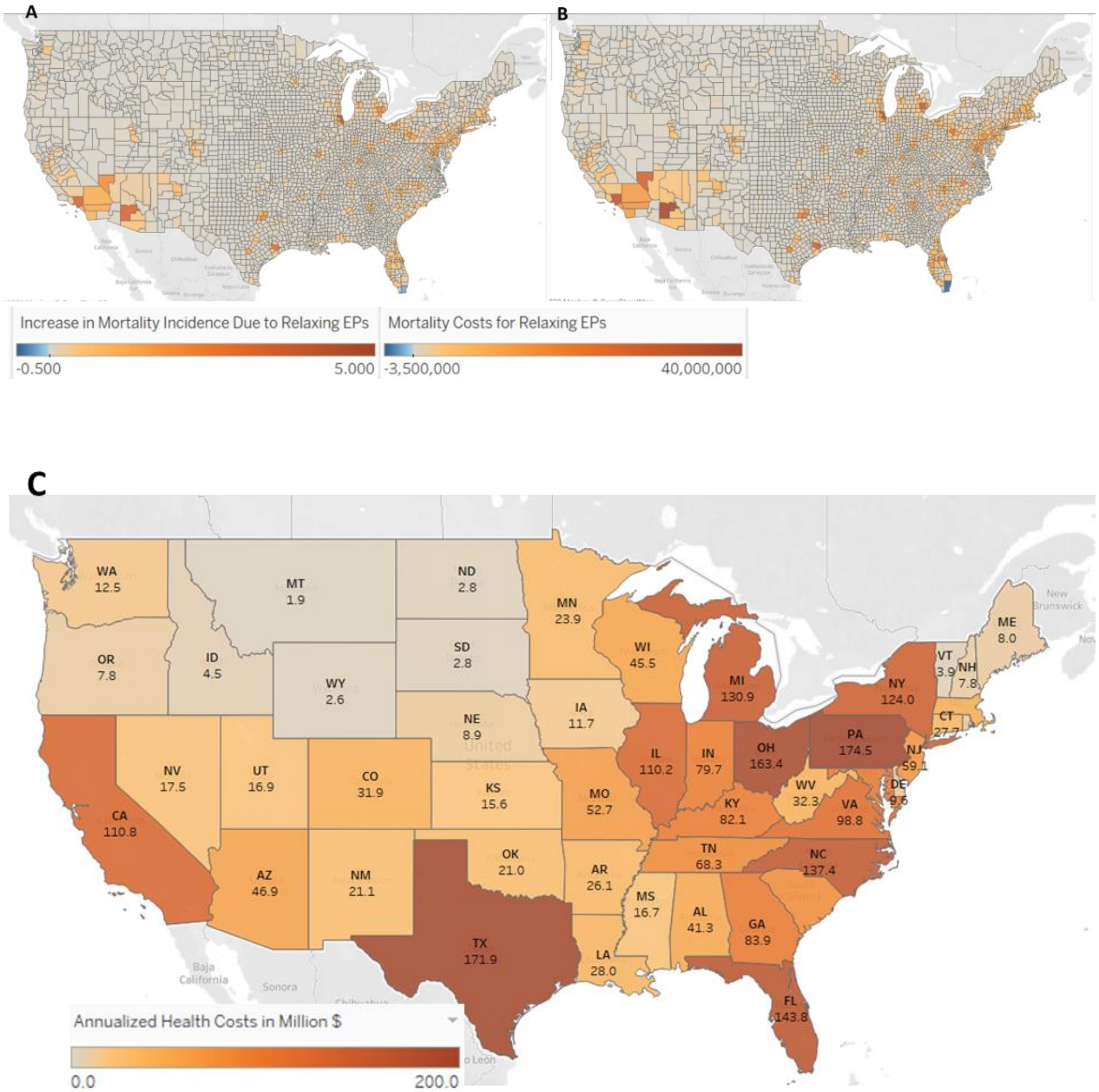
Figure 2-8 Spatial distributions of nonattainment counties

(A) Temporal trends of NNA60 under EP-RELX and RCP8.5 climate (red) and under EP-CONT without considering climate change (black). P1 and P4 correspond to those in Figure 2-7B. (B) Nonattainment counties in 2050 under EP-CONT with the current climate, corresponding to P1 in Figure 2-5. (C) Additional counties in nonattainment corresponding to the shift from P1 to P4 under RCP8.5. This change represents the net impact of EP relaxation and climate change on NNA.

2.5.5 Monetized health costs due to relaxing EPs and climate change

The increases in ozone levels lead to higher mortality incidences and higher health costs. According to the ozone concentration predictions, I calculate the increase in mortality and costs due to relaxing EPs and climate change by counties (Figure 2-9). To avoid the single-year effect, the costs are annualized by taking the 20-year annual average. Nationally, from 2030 to 2050, relaxing EPs lead most counties to increase health costs. The national annualized additional costs are 2.49 billion 2015$ for RCP8.5 and 2.47 billion 2015 $ for RCP4.5 and 2.30 billion $ in 2010 climate condition, respectively. The finding confirms that relaxing EPs, in general, causes additional health costs of over $2 billion per year, about $15 to 20 per year per household.

On the other hand, comparing health costs between RCP8.5 and RCP4.5 show that climate change triggers additional health costs for most counties and states. Nationally, relaxing EPs under RCP8.5 have higher annualized costs of $183.09 million per year, about a 7.4% increase from that without climate change. However, the distributions vary across different regions. In addition, the states also vary in terms of the effects of climate change. Unlike most states, Missouri, Indiana and Kentucky have lower health costs due to climate change, while California, Pennsylvania suffer much more, around 15-20% additional costs under RCP8.5. The regional differences show the complexity and heterogeneities of the designing policies related to emission control and climate change.


A
B
Increase in Mortality Incidence Due to Relaxing EPs
-0.500
5.000
Mortality Costs for Relaxing EPs
-3,500,000
40,000,000
C
WA 12.5
MT 1.9
ND 2.8
MN 23.9
OR 7.8
ID 4.5
SD 2.8
WI 45.5
WY 2.6
MI 130.9
NY 124.0
VT 3.9
NH 7.8
ME 8.0
IA 11.7
NE 8.9
CT 27.7
PA 174.5
OH 163.4
IN 79.7
IL 110.2
NJ 59.1
NV 17.5
UT 16.9
CO 31.9
KS 15.6
MO 52.7
WV 32.3
DE 9.6
KY 82.1
VA 98.8
CA 110.8
TN 68.3
OK 21.0
AR 26.1
NC 137.4
AZ 46.9
NM 21.1
MS 16.7
AL 41.3
GA 83.9
TX 171.9
LA 28.0
FL 143.8
New Brunswick
Baja California
Sonora
Annualized Health Costs in Million $
0.0
200.0

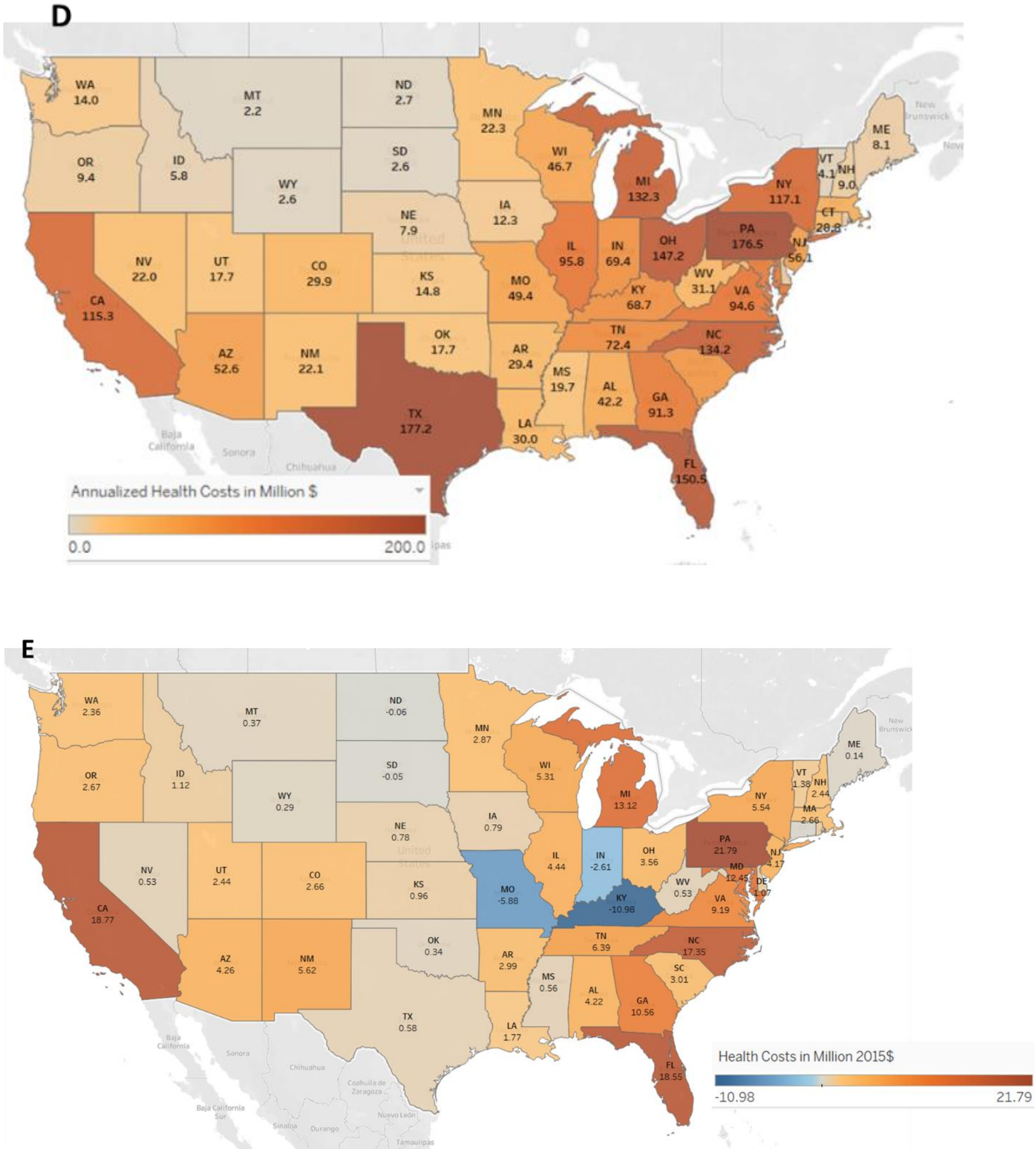


Figure 2-9 Spatial distributions of monetized costs

(A)2030-2050 annualized changes in mortality incidences and annualized health costs due to relaxing EPs for RCP4.5 by counties. (B) 2030-2050 annualized changes in mortality incidences and annualized health costs Due to relaxing

EPs for RCP8.5 by counties. (C)2030-2050 annualized changes in mortality incidences and annualized health costs due to relaxing EPs for RCP4.5 by states. (D) 2030-2050 annualized changes in mortality incidences and annualized health costs Due to relaxing EPs for RCP8.5 by states. (E) Additional annualized Costs of Climate Change on Health Costs of Relaxing EPs. This change represents the net impact of EP relaxation and climate change on monetized health costs

2.6 Policy implications and discussions

In general, this study highlights critical relationships in intricate modeling systems, thereby enabling insights that might otherwise be obfuscated or overlooked. By applying complex integrated models of energy policies, climate systems, and health evaluations, policymakers can better understand the complexity of features that influence policy markets in the energy-related economy. The following section explains these policy implications in detail.

First, my research confirms the significance of continuing the EP policies on ozone standard control and achieving better public health. Although ground-level O_3 in the U.S. has seen a substantial decline over the last several decades due to enduring emission mitigation efforts, our assessment suggests that a continuing decline in the O_3 should not be taken for granted. The DDM-based isopleth diagram demonstrates the potential for an upsurge of NNAs under EP-RELX starting from around 2034 (Figure 2-7). As a result, the NNAs in 2050 could roll back to the levels projected for 2021–2022 (Figure 2-7A). The clear difference in NNAs between *P1* and *P4* in Figure 2-7 and 2-8 reflects the important roles of EP relaxation and climate change in regulating the status of NNAs. EP relaxation and climate change increase both NNA_{70} and NNA_{60} by more than three-fourths in 2050. Of the projected increase in NNA_{60}, 40% is attributed to EP relaxation, 35% to climate change, and 25% to EP and climate synergy. This will mean extra 5.7 thousand mortality in total, correspondingly about 2.5 billion dollars health costs per year through 2030 to

2050, equivalent to about 0.01% of the national GDP in 2018. Although the yearly health cost is comparably small relative the national scale of the economy, it should be neglected. Overall, the result reflects the need for more outstanding efforts to mitigate O_3 under the relaxation of EPs.

Second, my study confirms the existence and magnitude of the synergistic effect between the energy policies with climate change. In specific, the study shows that the projected increases in OPE due to climate change magnify the increase in O_3 under EP relaxation and increase the effectiveness of NOx abatement for reducing O_3, therefore ensuring the appropriateness of extending mitigation efforts in the context of climate change.

This synergistic effect has broader policy implications. It calls for closer scrutiny of the relationship between energy policies and climate change mitigation efforts. As the world's largest economy and the second-largest emitter of CO_2, the United States plays a leading role in the international community catalyzing cooperation on climate change. The 2014 U.S.-China joint announcement on climate goals, for example, helped set the stage for the success of the United Nations Climate Conference in Paris, encouraging 190 other countries to put forward climate actions of their own. A relaxation of EPs by the United States chills these global actions, with broad implications for climate. Previous studies revealed substantial health and ecosystem co-benefits of stringent EPs from the EP-induced reduction in air pollutant emissions. To isolate the health and ecosystem impacts, these co-benefit studies often hold climate constant. A recent study found that the health co-benefits can originate from the reduction of co-emitted air pollutants and the slowing of climate change, representing two separate mechanisms linking EPs to air quality. I show further that these two mechanisms are synergistic, with a larger synergistic effect on O_3 under the more intensive warming scenario. The magnitude of this synergistic effect demonstrates the critical need to conduct assessments of EPs in the context of the global climate system when evaluating the resulting impacts on local air quality and associated health benefits/disbenefits.

Third, the energy policies will impact the regions differently depending on their current energy mix, available energy resources, and climate conditions. This regional heterogeneity creates different standpoints for regional policy discussion dynamics - the policy winners, which are affected more positively by the energy policies, may show more supports for the EPs and possibly more stringent policies. In general, all counties, other than the two in Florida, are forecasted to be negatively affected by relaxing EPs. However, some regions like California ($ 115.3 billion per year), Texas ($177.2 billion per year), Pennsylvania ($176.5 billion per year), and Florida ($150.5 billion per year) are relatively more negatively affected by relaxing EPs than mid-West states. In addition, adding climate change effects may further complicate the standpoints of the states. For example, the RCP8.5 scenario casts more health costs in some regionals, including California ($18.8 billion per year), Florida ($18.6 billion per year), and Pennsylvania ($21.8 billion per year), but introduces little costs for Texas and even negative impacts in Indiana, Kentucky, and Missouri. The findings show that climate change affects regions differently due to the complexity of the climate systems. This regional heterogeneity calls for specific regional transfer mechanisms to be discussed or considered when enacting uninformed national policies.

Last, acknowledging the uncertainties, the importance of the EP policies can be higher than estimated in this study, given that this study has used modest, conservative assumptions. Efforts are made to identify and mitigate sources of uncertainty in my analyses. For example, sensitivity tests with different socioeconomic assumptions are conducted to bound the role of EP relaxation in air pollutant emissions. Multi-year means are used to smooth the interannual climate anomalies under two climate scenarios (Materials and Methods). However, more uncertainty lies in our ability to project future meteorology and emissions. For example, Sillmann *et al.* found substantial differences in projected changes in climate extremes (e.g., the number of warm days) among models, indicating that the simulated frequency and severity of high-O_3 days may differ by substitution of meteorological conditions projected by other climate models. In addition, we only consider a subset of EPs, while relaxation of other EPs and future additions of EPs would further contribute to the changes in pollutant emissions. Nevertheless, with all the sensitivity tests and simulations conducted, the overall relationships between EP/climate and O_3 attainability remain robust to the sources of uncertainty investigated (Figure S3).

Going forward to inform better policy implications, this study will be further completed in two directions. The first direction is to explore more sensitivity analysis into the monetized benefits associated with EP-continued scenarios and conduct thorough cost-benefit research. This study explains how relaxing EPs lead to higher health costs, but I did not fully estimate the compliance costs to complete a more concrete cost-benefit framework. In addition, the second way to improve the current study is to discuss the regional inequality revealed in the ozone standards, adding to the discussions of the regional winners and losers of the EP policies.

2.7 Appendix 2A. Supplemental Materials

2.7.1 Supplemental Figures

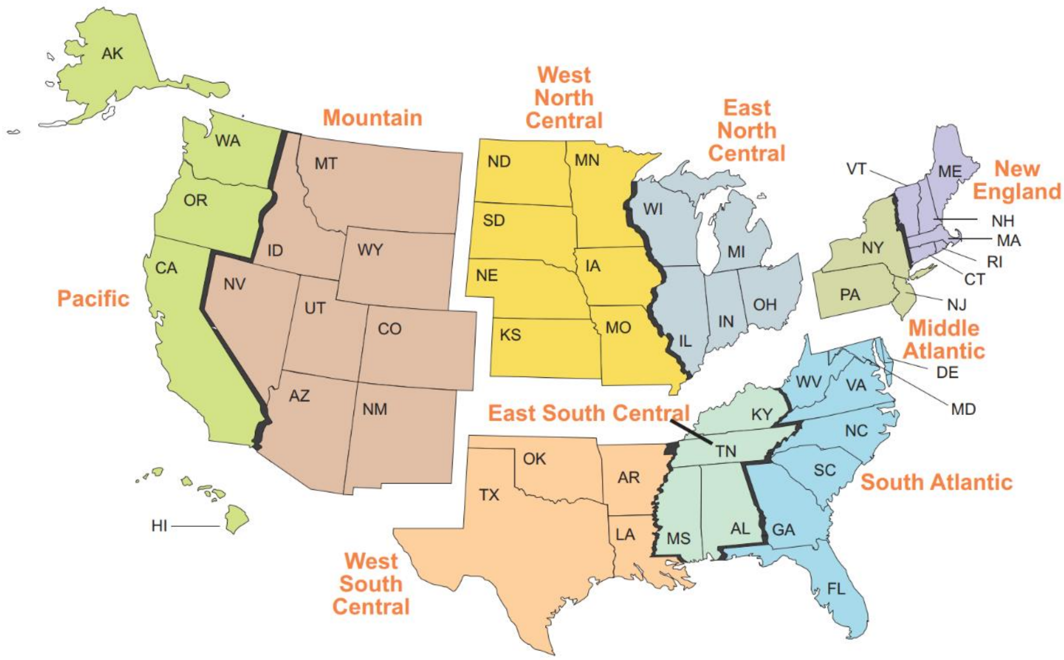


Figure S1. GT-NEMS region definition (Source: US EIA).

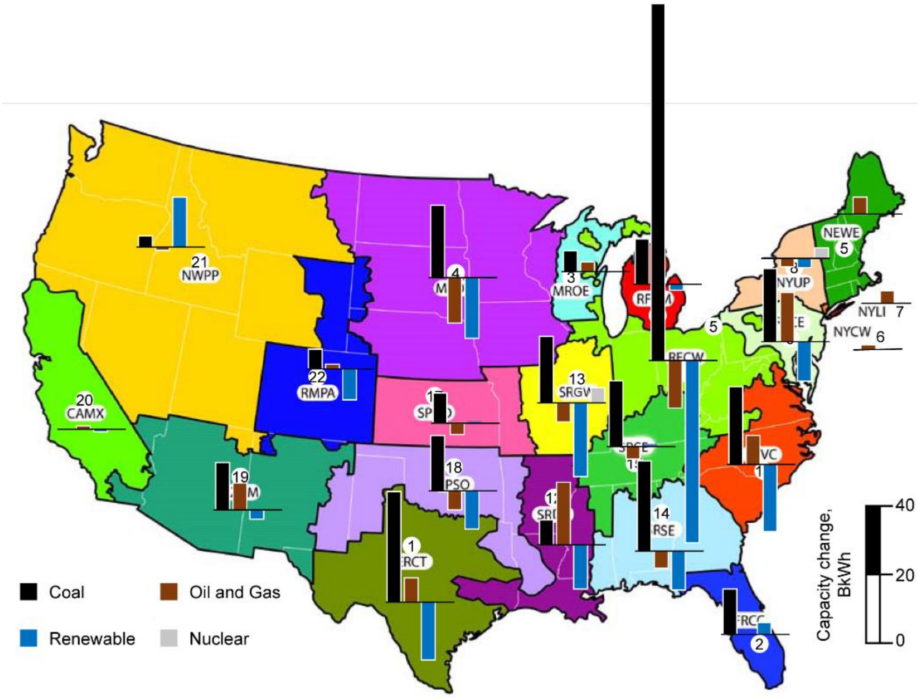


Figure S2. Regional changes in electricity capacity by fuel type in 2050 due to relaxation of EPs.

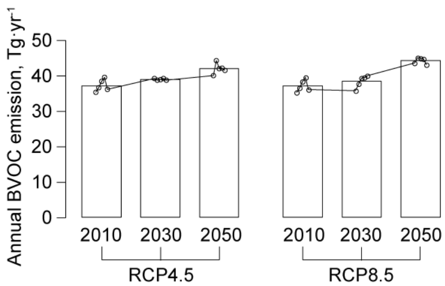


Figure S3. Annual total BVOC emissions in 2010, 2030, and 2050 under RCP4.5 and RCP8.5

(Related to Figure 2-3). Five-year means are shown as boxes; individual years are shown as circles.

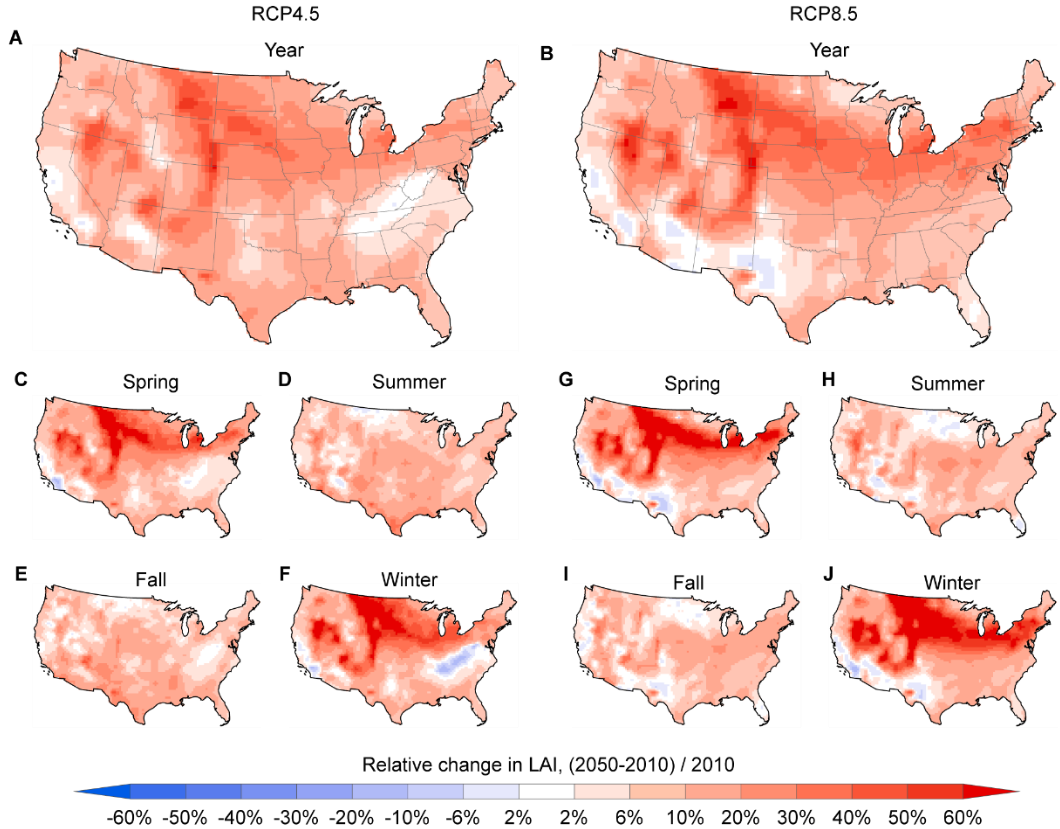


Figure S4. Spatial distributions of relative changes in LAIs between 2010 and 2050.

Ensemble means of CESM1 outputs from multiple simulations are used to characterize LAIs in 2010 and 2050 periods. (A) and (B) show the relative changes for the entire year under RCP4.5 and 8.5, respectively. Other panels show those for individual seasons. Results show that although RCP8.5 represents higher increase in annual average LAIs than RCP4.5 in most areas, the LAI increases in the summer in most regions and fall in certain regions in the west tend to be lower under RCP8.5 than under RCP4.5.

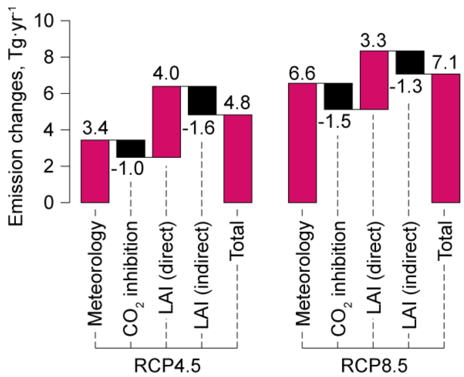


Figure S5. Attribution of changes in BVOC emissions between 2010 and 2050 to changes in individual driving factors.

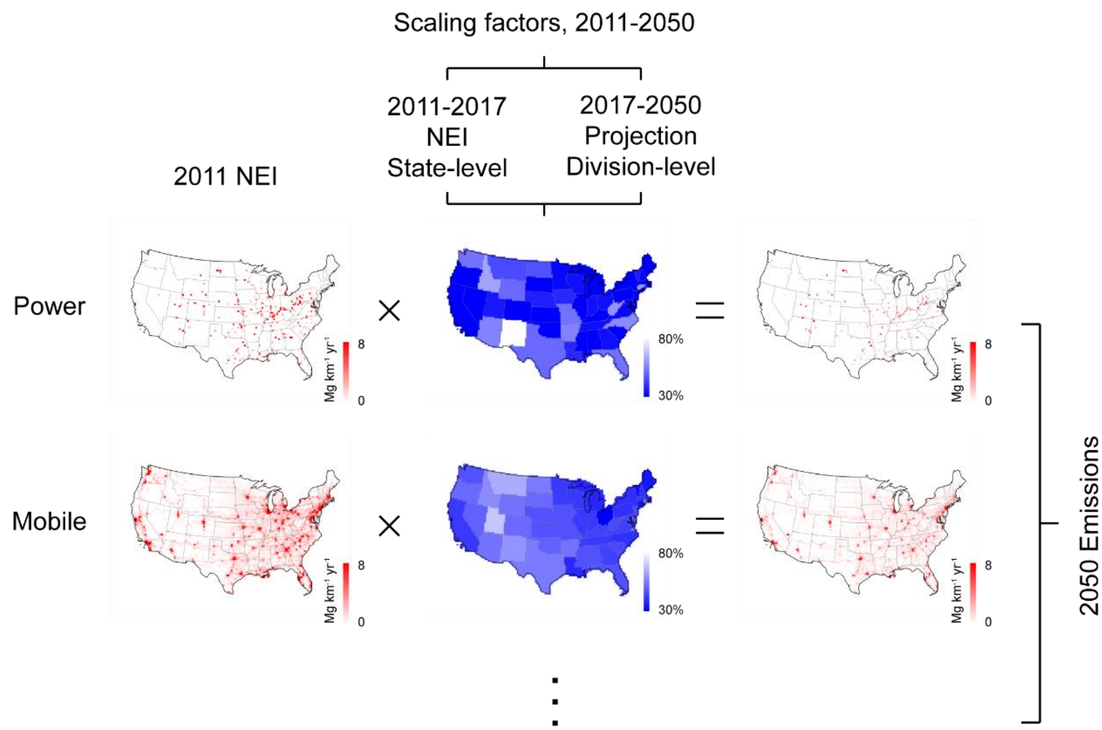


Figure S6. Schematic of the scaling method to derive spatially-resolved future emissions for air quality modeling

The schematic uses NOx emissions under EP-CONT as an example to show how spatially-resolved future emissions are derived.

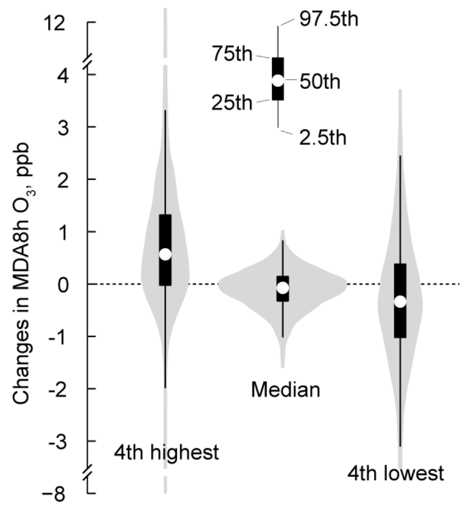


Figure S7. Changes in the annual 4th highest, median, and 4th lowest MDA8h O_3 due to the climate change between 2010 and 2050 under RCP8.5.

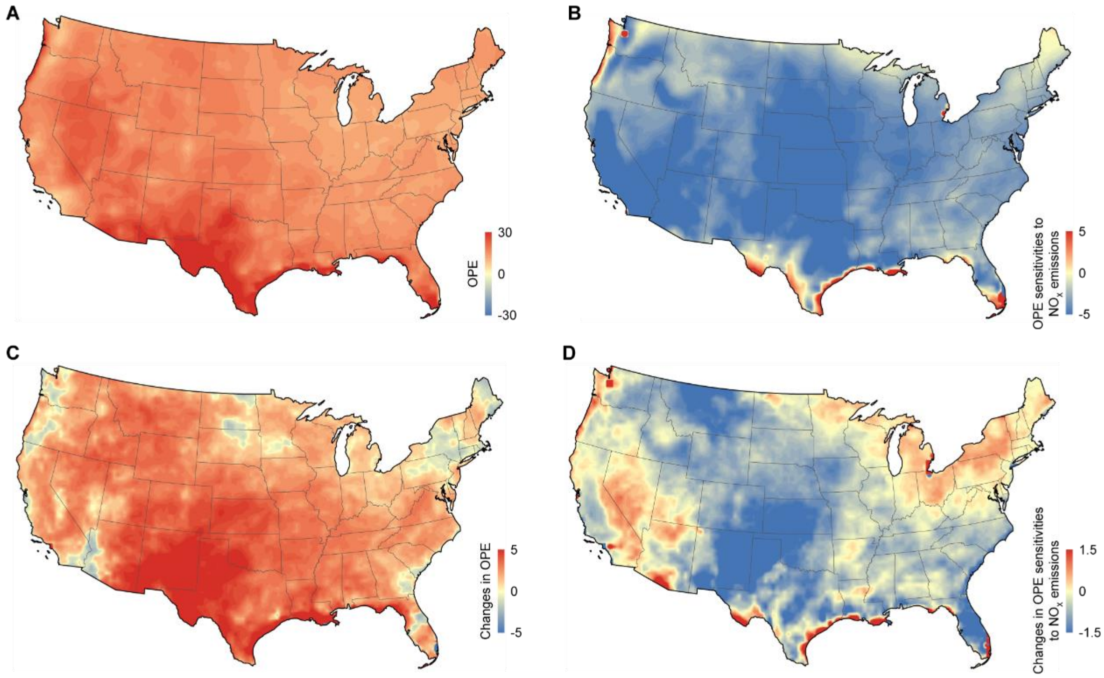


Figure S8. Spatial distributions of OPE

(A) and the OPE sensitivity to NOx emissions (B) in 2050 under RCP8.5 and spatial changes in OPE (C) and the OPE sensitivities to NOx emissions (D) due to climate change between 2010 and 2050 under RCP8.5. The OPEs are the averaged values over high-O_3 days (i.e., the 10% days with highest MDA8h O_3).

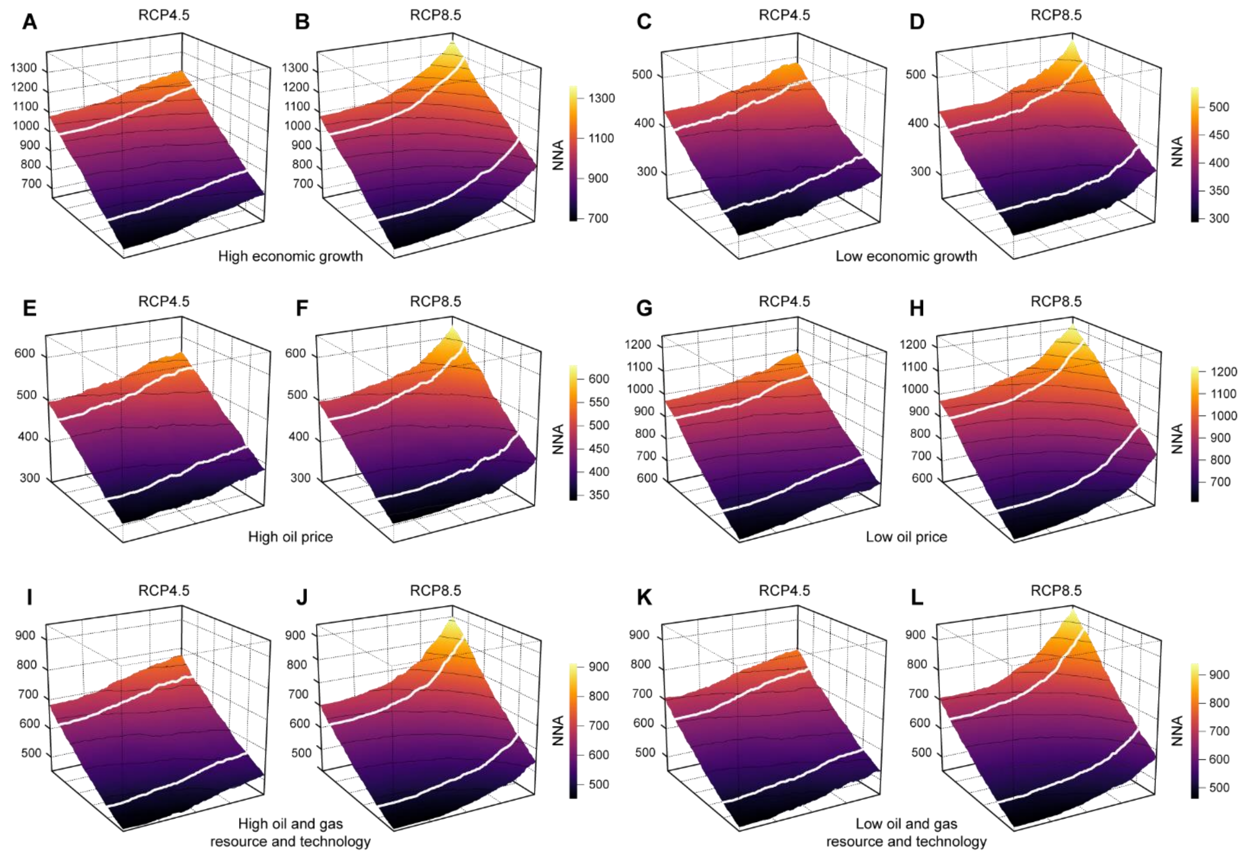


Figure S9. Impacts of EP relaxation and climate change on NNA under alternative assumptions adopted in energy projections

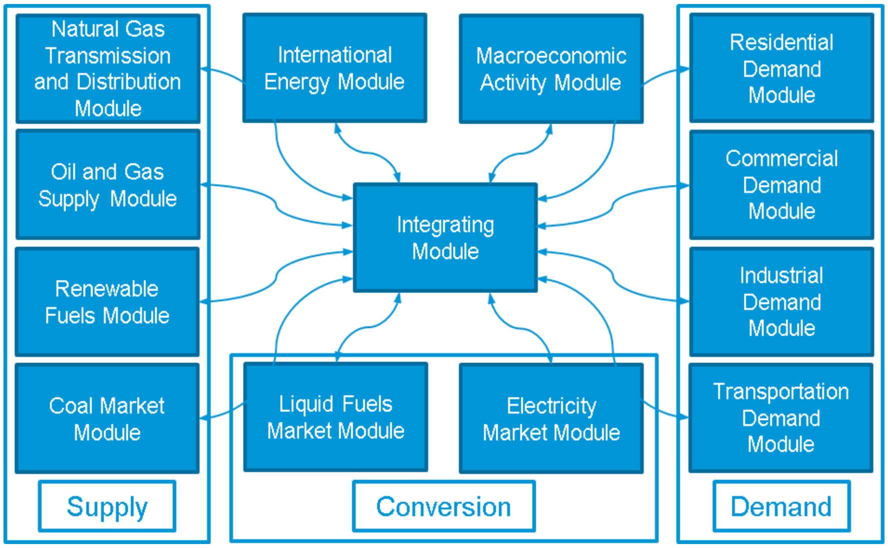


Figure S10. The modular structure of GT-NEMS (Source: US EIA)[2].

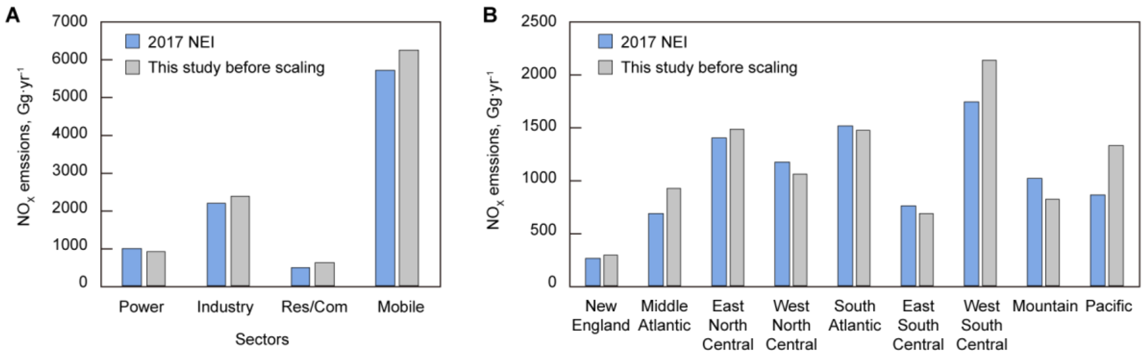


Figure S11. Comparisons of NOx emissions between NEI and our estimates

(A) by sector and (B) by region. The comparisons are conducted for the year 2017 which is the base year of our energy and emission projections.

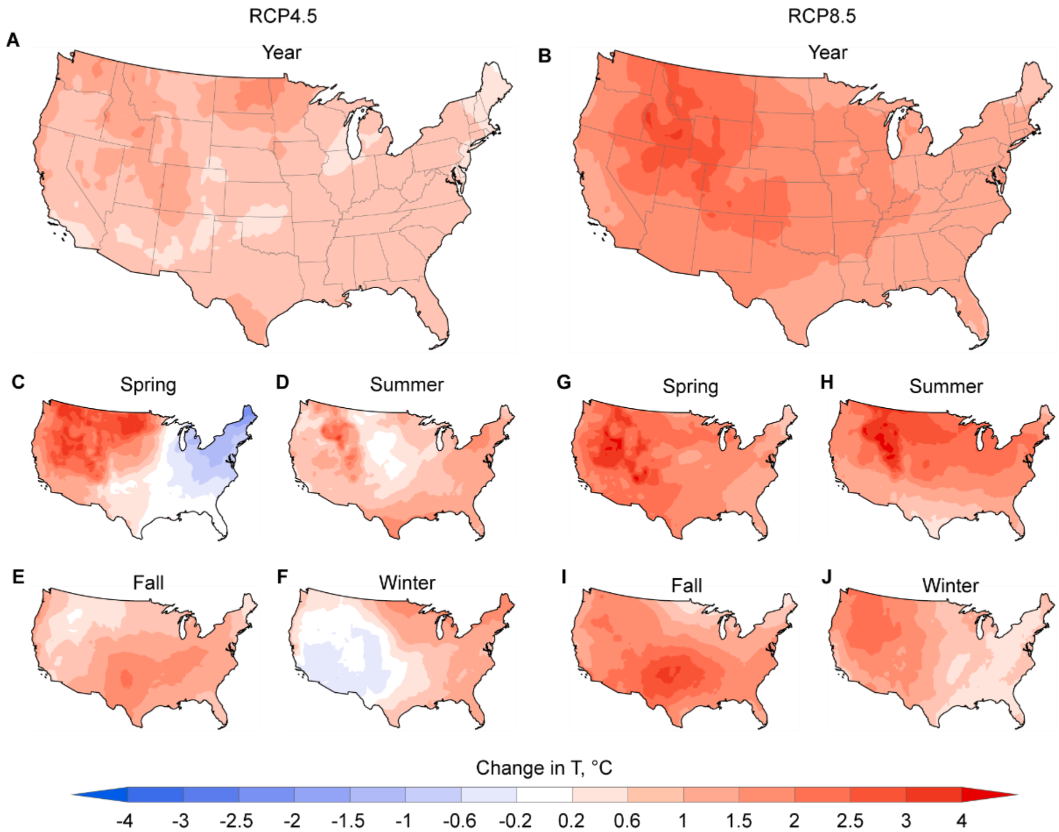


Figure S12. Projected changes in 2-m temperature between 2010 and 2050

The 2010 and 2050 periods contain five years each (2008-2012 and 2048-2050). Temperature levels are averaged over the five years. The changes are calculated as the level in 2050 minus that in 2010 and are calculated for both RCP4.5 (A, C, D, E, and F) and RCP8.5 (B, G, H, I, and J). (A) and (B) show the temperature changes for the entire year. Other panels show those for individual seasons.

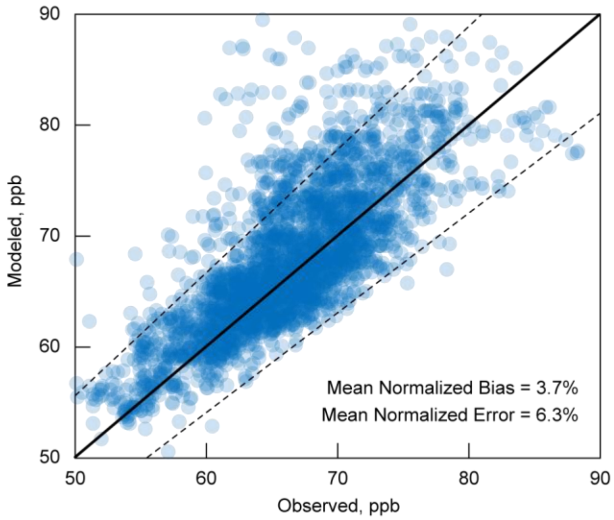


Figure S13. Comparison of the annual 4th highest MDA8h O_3 between observations and model simulations by county

County-level CDC data were plotted against our modeled results. The observed values derived from the CDC dataset represent the average values of the annual 4th highest MDA8h O_3 over the 5 years between 2009 and 2013. The dashed lines are ±10% lines.

2.7.2 *Supplemental Tables*

Table S1. Summary of the EP scenarios.

Scenario	**Description**
EP-CONT	Assumes trend improvement in known technologies and unchanged implementation and sunset dates of current laws, environmental regulations, and international protocols that are available as in September 2017. The impacts of proposed legislation, regulations, and standards are not included with the exception of the following EPs. A list of the legislation and regulations included in GT-NEMS can be found in Data S1. 1. CPP enforcement and extension: Assumes that the CPP will proceed as enacted between 2022 and 2030 and be extended after 2030 through 2050, which result in power sector CO_2 emissions continue to decline to achieve a 50% reduction below 2005 levels in 2050; 2. PTC/ITC extension: Extends PTC (for wind, geothermal, conventional hydropower, biomass, and eligible technologies) and ITC (for solar and wind) through 2050 at full value; 3. New efficiency requirements in transportation, residential, and commercial sectors: Increases the Corporate Average Fuel Economy (CAFE) and greenhouse gas (GHG) emissions standards at an annual average rate of 0.4% beyond 2025 in the transportation sector; includes additional updates to federal efficiency standards for residential and commercial major end-use equipment according to the timeline in the U.S. Department of Energy multiyear plan[4] and is also applied to a range of products that are not currently being covered.
EP-RELX	Stems from EP-CONT with the following changes: 1. CPP elimination: assumes that CPP is permanently voided and is not replaced by other controls on power sector CO_2 emissions. 2. Early PTC/ITC sunset: Eliminates the PTC and the ITC in 2019, earlier than the current schedules; 3. No new efficiency requirements in transportation, residential, and commercial sectors: Freezes the CAFE and GHG emissions standards at 2021 levels; removes the federal efficiency standards that are slated to go into effect after 2018 for residential and commercial major end-use equipment.

Table S3. Total anthropogenic emissions of criteria air pollutants in 2011 and future projections under EP-RELX and EP-CONT in the United States, in Gg yr^{-1}.

Pollutants	**2011 NEI, Gg/year**	**2050 EP-RELX, Gg/year**	**2050 EP-CONT, Gg/year**	**Relative change, (RELX−CONT)/CONT**
SO_2	5,696	2,526	2,060	22.6%
NOx	12,523	7,863	7,380	6.5%
CO	44,627	21,137	20,255	4.4%
VOC	10,914	9,214	8,992	2.5%
PM_{25}	1,698	1,542	1,493	3.3%
PM_{10}	2,157	1,894	1,831	3.4%
NH_3	346	294	285	2.9%

Note: Emission values shown in the table do not include emissions from wildland/prescribed fires, dust, and agricultural cropland and livestock management.

Table S4. Impacts of EP relaxation on total NOx emissions in 2050 under different assumptions.

Assumptions	EP-RELX, Gg/year	EP-CONT, Gg/year	ΔE_{NOx}, Gg/year	ΔE_{NOx}/EP-CONT
Baseline	7,860	7,380	480	6.5%
High economic growth	8,660	8,130	530	6.6%
Low economic growth	6,980	6,580	400	6.2%
High oil price	7,280	6,840	440	6.4%
Low oil price	8,410	7,920	490	6.2%
High oil and gas resource and technology	7,690	7,350	340	4.7%
Low oil and gas resource and technology	7,830	7,390	440	5.9%

Table S5. Numbers of nonattainment counties for O_3 standards of 0.070 ppm (NNA_{70}) vs. 0.060 ppm (NNA_{60}) under different EP and climate scenarios.

Emissions	Climate					
	2010		2050 (RCP4.5)		2050 (RCP8.5)	
	NNA70	NNA60	NNA70	NNA60	NNA70	NNA70
2010	851 (737–970)	2680 (2614–2742)	–	–	–	–
2050 (EP-CONT)	27 (24–31)	497 (445–551)	32 (27–38)	564 (528–601)	37 (32–42)	631 (580–684)
2050 (EP-RELX)	30 (26–34)	650 (582–721)	44 (36–53)	739 (695–784)	49 (43–55)	879 (820–940)

Note: Numbers in parentheses show 95% confidence intervals of the NNA values. See Supplemental Experimental Procedures for how the NNA values and uncertainties are derived. P1 in Figure 4 corresponds to 2050 EP-CONT emissions with 2010 climate in the table; P2: 2050 EP-RELX emissions with 2010 climate; P3: 2050 EP-CONT emissions with 2050 climate; P4: 2050 EP-RELX emissions with 2050 climate.

2.7.3 Supplemental Experimental Procedures

The health impacts are estimated according to the framework developed for Environmental Benefits Mapping and Analysis Program (BenMap) by US EPA (USEPA, 2018). This framework, presented in Figure XX, starts from the ozone projected design values (DV) - annual fourth-highest daily maximum 8-hr O3 concentration averaged over 3 years (US EPA, 2019), which in this chapter are calculated previously. Population estimates up to 2050 and baseline incidence (mortality) rates are simulated using EPA's tool Population Simulation Model, PopSim. The next step is inserting these three sets of inputs into the preselected health impact function, from which health effect can be projected in terms of change (delta) in mortality incidence at county level for each year. Finally, adopting the value for statistical life that EPA summarized monetizes the health impacts into quantified benefits and costs estimates in terms of U.S. dollars. The following section will explain more details for each procedure.

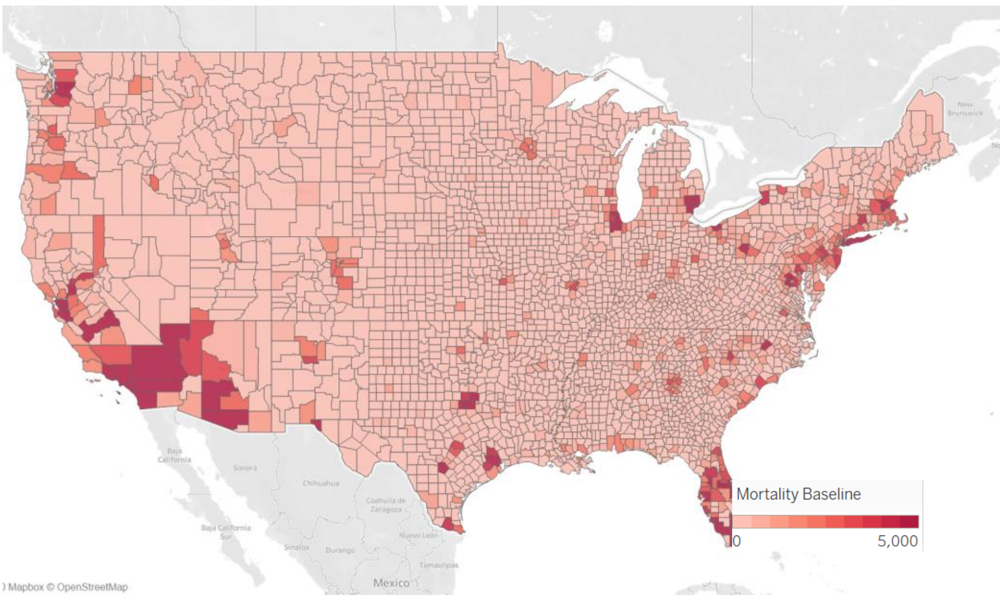
2.7.3.1 <u>Population and baseline incidence projections using PopSim</u>

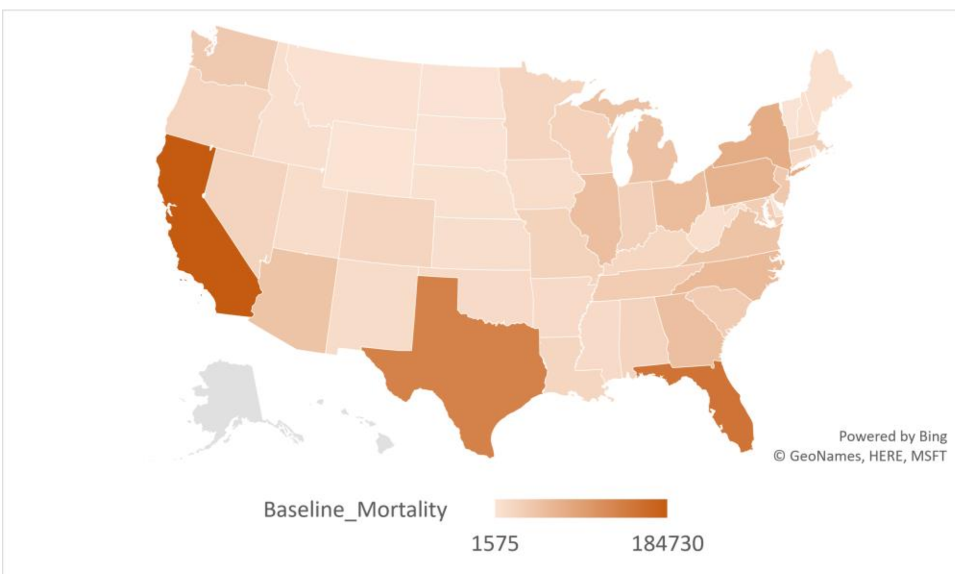
This Population Simulation model is firstly introduced and detailed described in Chapter 5 of EPA's "Second Prospective Study – 1990 to 2020 – Benefits and Costs of the Clean Air Act. U.S. Environmental Protection Agency, Office of Air and Radiation, April 2011."(USEPA, 2017). The main purpose of this model is to provide dynamic critical estimates inputs for mortality attributed to CAAA and then adopted as a supplement to EPA's other tools, such as BenMAP (USEPA, 2018).

The main inputs of the PopSim include the mortality effects of the air pollutants, mostly PM2.5, and incorporates a detailed life table from CDC on mortality by age, gender, and cause of death for years. Leveraging these inputs, it generates estimates for (USEPA, 2018)

- Simulate population in the U.S. by single year cohorts of age and gender for years between 1980 and 2050 under alternative assumptions about the degree of hazard posed by air pollution relative to baseline historical and projected Census mortality rates;
- Estimate changes in life years relative to baseline Census mortality rates;
- Apply air pollution hazards differentially by cause of death; and
- Analyze the effect of alternative cessation lag structures on the timing of total mortality and on total life years in the U.S. population, based on differential application by cause of death or other specifications of cessation lag

In our case, the default setting of EPA is used to simulate the future. The model uses aggregated Dose-Response function from Pope et al., 2002 (Pope et al., 2002) and a single default lag option. The PopSim baseline is presented as mortality incidence each year at the county level (Figure S14.). At the county level, the mortality incidence is quite diverse, ranging from less than ten incidences to more than 10,000 for 12 counties, averaging 511 nationally– mostly due to the differences in the baseline population for each county. Accordingly, the aggregate state-level mortality incidences show many similar trends. California, Florida, Texas rank top 3 states, with yearly death of more than 100,000, while the national average state yearly death is about 32,000.





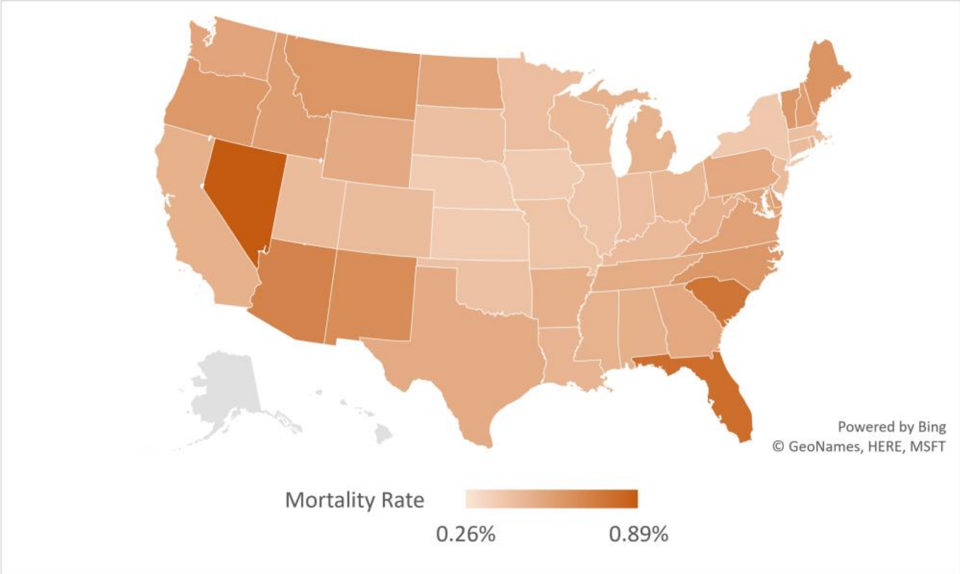


Figure S14. County-level (up) and state-level (middle) mortality baseline incidence and state-level mortality rates (bottom) in 2050

2.7.3.2 Health impact function

Health impact function will link the baseline mortality rate and the pollutant estimates to project future health incidences. Selecting an appropriate health impact function is one of the crucial part for health impact analysis since the evaluations will vary significantly with different parameters set in it.

In this chapter, only short-term mortality is considered and the core mortality function identified are recognized by US EPA (USEPA, 2018). EPA identifies two core health impact functions for ozone in terms of the short-term mortality and the most recent and comprehensive source is from Smith et al., 2009 (Smith et al., 2009), which is adopted in the evaluation processes in this study. The detailed descriptions of the functions can be found at US EPA BenMAP User

Manual Appendix F. [1] With the function set, plugging the ozone design values results in mortality incidence estimations, and the differences between various scenarios can be calculated.

Table S7 Core Health Impact Functions for Ozone and Short-term Morality identified by EPA

Effect	Author	Year	Location	Age	Co-Poll	Metric	Beta	Std Err	Form	Notes
Non-Accidental	Smith et al.	2009	98 U.S. cities	0-99	PM10	D8HourMax	0.000258	0.000167	Log-linear	Ozone season
All-Cause	Zanobetti and Schwartz	2008 b	48 Cities	0-99		D8HourMax	0.00050	0.00012	Log-linear	0-3 day lag, June-August, 1989-2000

Source: US Environmental Protection Agency (USEPA). (2018). Environmental Benefits Mapping and Analysis Program–Community Edition (BenMAP-CE): User manual appendices. page-1.

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[1] Smith et al. (2009) analyzed the relationship between daily mortality and ambient ozone concentrations through re-examination of evidence using the National Morbidity, Mortality, and Air Pollution Study (NMMAPS), which collected daily data on mortality, meteorology, and air pollutant concentrations for 100 U.S. cities from 1987-2000. The authors examined the sensitivity of city-specific ozone-mortality estimates to treatment of meteorology and co-pollutants, dependence on different ozone metrics, use of air conditioning, regional and spatial variability, and non-linear exposure-response relationship. Assuming a 10 ppb change in daily 8-hour maximum ozone concentration, he reported a 0.40 (0.22)% population-weighted change in non-mortality in a model without PM10.

2.7.3.3 Value for Statistical Life (VSL)

With the change in incidences identified, the final step is to apply VSL in the evaluation to finalize the monetizing benefits or costs in U.S. dollars. In my study, the VSL is adopted using EPA's estimates 8,705,114 in 2015$ regardless of the age, gender, geography (USEPA, 2018).

According to EPA (USEPA, 2018), this estimate is the mean of a distribution fitted to 26 "value of statistical life" (VSL) estimates that appear in the economics literature and that have been identified in the Section 812 Reports to Congress as "applicable to policy analysis." This represents an intermediate value from a variety of estimates, and it is a value EPA has frequently used in Regulatory Impact Analyses (RIAs) as well as in the Section 812 Retrospective and Prospective Analyses of the Clean Air Act.

Table S8. Core Unit Values for VSL based on 26 VSL studies identified by EPA

Basis for Estimate *	Age Range at Death		Unit Value (VSL) (2015$)	Distribution of Unit Value	Parameters of Distribution	
	Min	Max			P1	P2
VSL, based on 26 value-of-life studies	0	99	8,705,114	Weibull	9,648,168	1.509588

Source: US Environmental Protection Agency (USEPA). (2018). Environmental Benefits Mapping and Analysis Program–Community Edition (BenMAP-CE): User manual appendices. Page H-2.

After the VSL is set, the mortality incidences can be multiplied by VSL to be monetized. The differences between the various scenarios illustrate the monetized avoided costs, or benefits due to ozone decreases; or in other words the monetized cost due to ozone increases.

Following US EPA's guidance, the VSL based on 26 previous studies show Weibull distribution with 90% confidence intervals of 1.349M to 19.957M, which is 16% to 229% times of the unit value 8.7 million.

Since the VSL is uniformly applied to all age and all regions, the health impact evaluations very alter according to have 90% confidence interval of 16% to 229% times of their current estimates, which introduces a large range of uncertainty.

I acknowledge that the way of using VSL adopted by US EPA and other federal agencies does not differentiate by age, which contradicts the suggestions from some economists (Freeman, 1992; Muller & Mendelsohn, 2007). Instead of uniformly value applied to all age, they advise adjusting the VSL according to the expected remaining life of the influenced population, since air pollution often affects elder population more. One of the most common ways to adjust the VSL is to calculate the value of a year life using discount rate, and add-up the discounted value of future years of life weighted by the probability of surviving rates (Muller & Mendelsohn, 2007). In their work, they choose social discount rate to be 3% and estimates life expectancy for each age-cohort using mortality statistics from the National Center for Health Statistics. In their study, they show that these options, whether to apply age adjustments and what levels of discount rates, alter their health benefits significantly. They reports using US EPA VSL but adapted to different ages increases the estimates by 152%, and US EPA method will increase the estimates by 272% in U.S. for all criterion pollutants (Muller & Mendelsohn, 2007).

The results show an age-differentiated VSL may significantly alter the health benefits evaluations. However, since we don't have an age-differentiated health impact function for ozone recognized by US EPA, this study sticks to the most conservative estimates of VSL – the US EPA’s methods for ozone-related health impacts.

2.7.4 Example: Health impact evaluation due to relaxing EPs in 2050 and RCP 8.5 for Fulton County, GA

First, the example starts from the projects from air-quality model that in 2050 under RCP 8.5, the design values for ozone in Fulton, GA is 63.71 ppb and 62.46 ppb respectively for relaxing EP scenario and continuing EP scenario, which shows relaxing EPs increases ozone design value by 1.26 ppb, noted as “Δ”.

The next step is to apply the ozone health impact function to get the incidence increase by adding Δ ozone concentration. As US EPA recommends, I adopt the function developed by Smith et al., 2009 is:

$$\Delta MI = \left(1 - \left(\frac{1}{Exp(\beta * \Delta)}\right)\right) * BIR * P$$

which: ΔMI is the mortality incidences change;

P is the population

β is paremeter noted as 0.000257743 (Smith et al., 2009)

Δ is the change in the ozone design values

BI is the baseline incidence rates

The PopSim estimates in 2050 the baseline mortality rates is 0.4479%. Multiplied by the population estimates, PopSim outputs the baseline mortality incidence to 2623.29 per year, noted as baseline incidence rates. Inserting the Δ and BI, the changes in mortality incidences is 0.85041793 in 2050. Finally, multiplying the mortality incidences calculated by the VSL, then the final health cost from relaxing Eps is \$7.4 million for Fulton County.

CHAPTER 3. SECTORAL-ECONOMIC DEVELOPMENT CASE STUDY: THE SHORT-TERM IMPACTS OF ELECTRIC VEHICLES ON GRID OPERATIONS FOR THE SOUTHEAST, NEW YORK, AND CALIFORNIA

In the second study, I explore the co-benefits and co-costs from the EV adoption policies on electricity grid operations. The analysis focuses on the short-term, sectoral impacts, in which the electricity sector deals with the EV charging demand unexpected and passively without extra unit and capacity planning process. The primary analysis is done by constructing an integrated model combining an EV load estimation model and an electricity dispatch model for regional electricity generation to accommodate EV charging loads. First, according to National Household Travel Survey (NHTS), I estimate the hourly EV vehicle demand in Southeastern (SERC-S), New York ISO (NYISO), and California ISO (Cal-ISO) areas respectively in three scenario settings: "EV12.5", "EV25", and "EV37.5", which anticipates an EV penetration of the total fleets of 12.5%, 25%, and 37.5% respectively in the year of 2030. Then I construct the regional supply curves for different time slices to match with the electricity demands, including the EV charging loads developed under three scenarios. Combing the two parts, the integrated model sheds light on what resources are used for EV charging demands, how much the extra cost is and how much carbon dioxide is emitted from the corresponding electricity generation. Finally, the results of the three regions are compared and discussed. Based on the modeling results, several policy implications are provided.

3.1 Introduction

Electric vehicles have been widely adopted to replace fossil fuel vehicles with the help of the electric vehicle policies both internationally and in the U.S (Bloomberg NEF, 2019; McKerracher, 2018; US EIA, 2019). There is no doubt that electric vehicles may contribute significantly to mitigating carbon emissions. The electric vehicle policies will play a significant role in accelerating the adoption of alternative fuel vehicles. However, lacking a comprehensive understanding of the impacts of the EV policies has hindered the appropriate cost-benefit analysis for these EV promotion policies (Bloomberg NEF, 2019; McKerracher, 2018). Apart from carbon mitigation, EVs are projected to show various benefits - help to reduce the local pollutants, reshape the supply chain of the fossil fuel and the automobile industry, and provide both the challenges and opportunities for the power industry (Hawkins et al., 2013; Sierzchula et al., 2014; Yong et al., 2015). However, very sparse quantification efforts have shown reliable and systematic estimations on the existence and the magnitude of these co-benefits and co-costs from the EV policies.

Among these aspects, one topic has caught extensive attention and has been heated debate on - how the grid management of the electric utilities will be changed by the electric vehicles (c. On the one hand, previous literature has shown huge potentials to take advantage of electric vehicles as one type of the manageable resources, such as storage capacity, demand response, or reserve (Hawkins et al., 2013; Sierzchula et al., 2014; Yong et al., 2015). However, these studies failed to provide a systematic and concise quantification for the evaluations of the potential benefits. They acknowledged the uncertainty and intermittent generation pattern in renewable energy and the complexity of electric vehicles pose huge challenges for the quantifications of the influences associated with the EV policies (Buekers et al., 2014; Ma et al., 2012; Skerlos & Winebrake, 2010; Sovacool & Hirsh, 2009).

Besides, the regional heterogeneity of the EVs and the grid integrations has rarely been examined in previous research (Mohamed, 2019; Jiang 2017; Ma et al., 2012; Al-Alawi & Bradley, 2013b; Buekers et al., 2014; Choi et al., 2013). Various regions may have considerable differences in the fuel mix of the power generation and existing demand patterns. What's more, the electric vehicle charging portfolio may also show regional differences. Many of the previous regional studies have focused on one region, such as New York State (Mohamed, 2019), California (Jiang 2017; Ma et al., 2012), Virginia-Carolina (Hadley, 2006), and Pacific Northwest (Schneider et al., 2006). However, one particular study, Choi et al., 2013 simulates the unit commitment model and economic dispatch models and examines the six regions in the Eastern Interconnection. It compares the electrical generating capacity, generating sources, electricity cost, and greenhouse gas emissions between each region in 2030. This study illustrates the influences of the EVs on the power grid vary by region significantly. For example, in the scenario assuming the EV sales to reach 100% by 2025, without controlled charging, Northeast Power Coordinating Council is projected to increase its natural gas and wind generation to satisfy the incremental demand, while SERC Reliability Corporation (SERC) reduces generation from natural gas but increase its reliance on coal generation in 2030. More studies are needed to verify the existence of the regional heterogeneities, examining different regions and considering updated practices from both the consumer charging behavior and the grid management.

Furthermore, various studies also reveal the differences between short-term 'passive' and long-term 'active' roles that the utilities can participate in EV charging (Arias & Bae, 2017;

Azadfar et al., 2015; Pradel et al., 2016; Sun et al., 2015; Tan et al., 2016b). In the short term, the electric grid will only treat EV as a source of electricity demand without further unit planning and coordination. While on the long run, several studies have shown the more potential cost-savings both for the EV owners and the utilities with appropriate planning, advanced technology, and innovative business models (Choi et al., 2013; Arias & Bae, 2017; Azadfar et al., 2015; H. Wang & Wang, 2014; Zhou et al., 2016, 2016).

3.2 Motivation/Research questions

In this research, I start to address the puzzle by quantifying the co-benefits and co-cost associated with the interaction between grid management and EVs. This study sheds light on the more systematic and comprehensive evaluations of the potential impacts of EV policies on the power grid planning and management for the utilities. In particular, this study illustrates if the power grid does not anticipate the massive needs of EV charging demands or simply ignores and fails to plan its generation units accordingly, what influences are cast on the grid operation costs and its carbon dioxide emissions. Filling the current research gaps, this is the initial step to check the rationale that if the grid has the incentives to adapt to the high EV penetration future at various regions.

Specifically, in this study, I estimate the short-term, sectoral impacts of EVs on the Southeast, New York ISO, and California ISO territory of the U.S. The detailed research questions are framed as:

What are the influences of electric vehicle charging demand on short-term grid operation cost for Southern company territory, New York ISO, and California ISO?

Correspondingly, what are the influences of electric vehicles on CO_2 *emissions from the electric power sector and the transportation sector?*

3.3 Hypotheses

Based on the literature reviews, the details of the hypotheses are:

Hypothesis 3.1: In the short term, the policy-driven electric vehicle penetration could increase the operation cost for the grid since the extra electricity demand from the EV charging would be met by consuming fossil fuel resources, mostly natural gas.

Hypothesis 3.2: In the short term, the policy-driven electric vehicle penetration could increase the CO_2 ***emissions from the electric power sector but reduce more*** CO_2 ***emissions from the transportation sector, thus decrease the overall net*** CO_2 ***emissions.***

Correspondingly, to examine Hypothesis 3.1, the measurements that I examine include overall O&M costs and average O&M costs per generation. To test Hypothesis 3.2, the electric power sectoral additional CO_2 emission and average CO_2 emission per generation resulting from EV charging are estimated. To further do the comparison, I also examine the net CO_2 emission effect considering the electricity generation and the avoided gasoline usage from EV replacement of the gasoline internal combustion engines.

3.4 Methodology

The methodology is detailed explained in this section. Firstly, I will briefly describe the research region. Afterward, the general research frameworks will be presented as the guidance of the organization of this research memo.

3.4.1 Research area

The research selects three areas as the case studies. The first area is the Southeastern region of the U.S., which is the SERC Reliability Corporation / Southeastern (SRSE or SERC-S) in the NERC region map. It is also known as the Georgia-Alabama region since it mostly covers these two states. Instead of the state boundaries, the region has been selected in NERC region as the reality of the power grid balancing authority. The SRSE region is balanced by the Southern Company for grid management which consists of 4 sub utility companies— Alabama Power, Georgia Power, Gulf Power, and Mississippi Power, serving more than 4.5 million retail customers. In other words, the SERC-S region does not go through the process of deregulation; thus, Southern company is the sole provider of the generation, transmission, and retails of the electricity for the region.

Unlike SERC-S, where the power system is vertically integrated and the physical sales are made bilaterally, the other two regions are selected to reflect deregulated electric power markets. The second area is the New York Independent System Operator (NYISO), the organization responsible for managing New York’s electric grid. Its serving area covers the majority of New York City and part of the New York state covering 19.8 million customers. Since the power market is deregulated in the region, NYISO does not own the generators or involve in the retails. Instead, NYISO operates wholesale power markets that trade electricity, capacity, transmission congestion contracts and administers auctions for the sale of capacity. Thus, the area represents deregulated power market different from SERC-S.

The third area is the California ISO, which serves 80% of the country’s most populated state and a small part of Nevada. Unlike SERC-S and similar to NYISO, the region is deregulated and has a competitive wholesale electricity market. Besides, California is an important player leading the transportation revolutions. Its fragile grid system has been under huge pressure to deal with the state's efforts to move to the low-carbon future. Thus, the area is worthy of exploring and selected to compare with the other two regions.

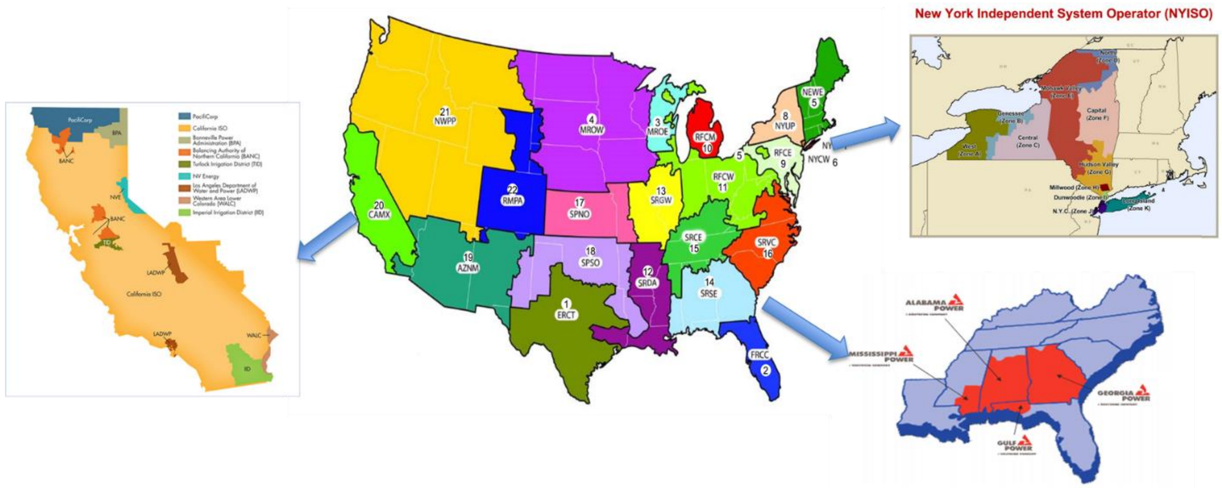


Figure 3-1 The NERC region map and the three focus areas

3.4.2 Research structures

To evaluate the short-term effects, the general framework of this study is shown below. To estimate the hourly demand of the EVs, two separate analyses – the probability models for individual charging behavior and the overall adoption numbers of EVs are constructed. Meanwhile, derived from the projected demands excluding the EVs and the generation resources available at certain time slices, the grid dispatch practice can be predicted and thus, the cost curve can be estimated. Lastly, the final impacts of EVs on the grid operations are evaluated when matching the hourly demand from the EVs and the grid dispatch supply curve.

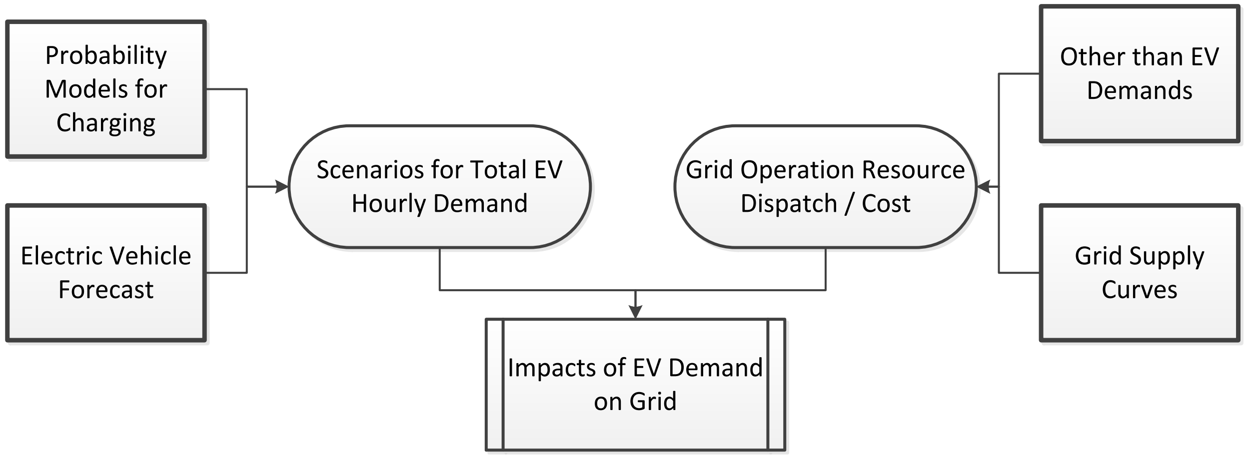


Figure 3-2 The framework of this study

3.5 Results

This section presents the results on each part of the general framework shown in Figure 3-2. - electric vehicle demands, electric vehicle charging curve, the regional power grid demand, and generating resources. Lastly, the integration of EV demand and the power grid supply is matched to evaluate the final results.

3.5.1 Electric vehicles demand

This section forecasts the electric vehicle demand in the various scenarios. The total demand is a function of the total volume of EVs with the charging profile identified for each hour of the day. In the following section, each part of the equation is examined.

3.5.2 Electric vehicles sales and stocks

Firstly, we need to examine the trends in the sales of electric vehicles over time. The U.S. monthly sales are presented in Figure 3-3, and it shows that the sales have been growing rapidly over time. In addition, the percentage of the EV to all vehicle sales has been increased dramatically as well. The current level of the EV percentage of the total sales is over 1.5%.

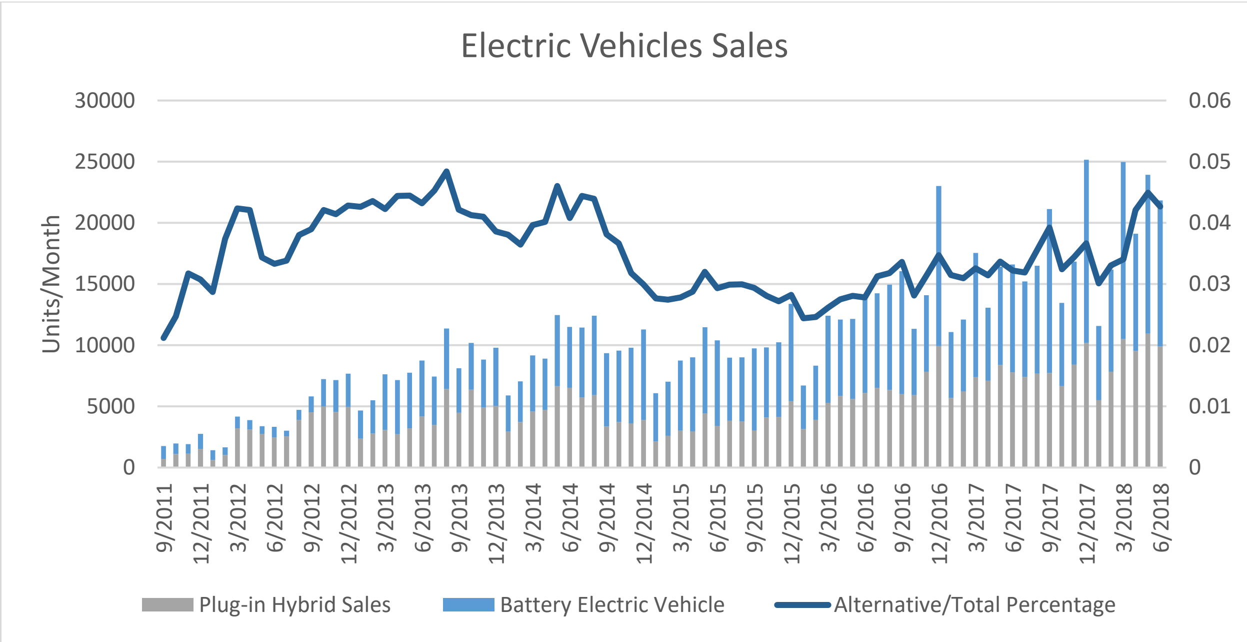


Figure 3-3 Electric vehicle historical sales in the U.S.

Source: Bloomberg Terminal, 2019

However, various forecasts have projected the EV penetration increase at a substantial pace. Bloomberg (McKerracher, 2020) estimates that the sales of plug-in electric cars are going to increase tremendously, reaching 28% of all vehicle sales annually by 2030 and 58% by 2040. One study summarizes the recent forecasts of EV uptakes in 2040 (Kapustin & Grushevenko, 2020). The majority of the estimates, from IEA (International Energy Agency), EV outlook, BP, and OPEC, projects the share of EV to all the vehicle stock around 15% to 46%. In contrast, International Renewable Energy Agency (IRENA) forecasts more radical EV adoption up to

80% of the total fleet.

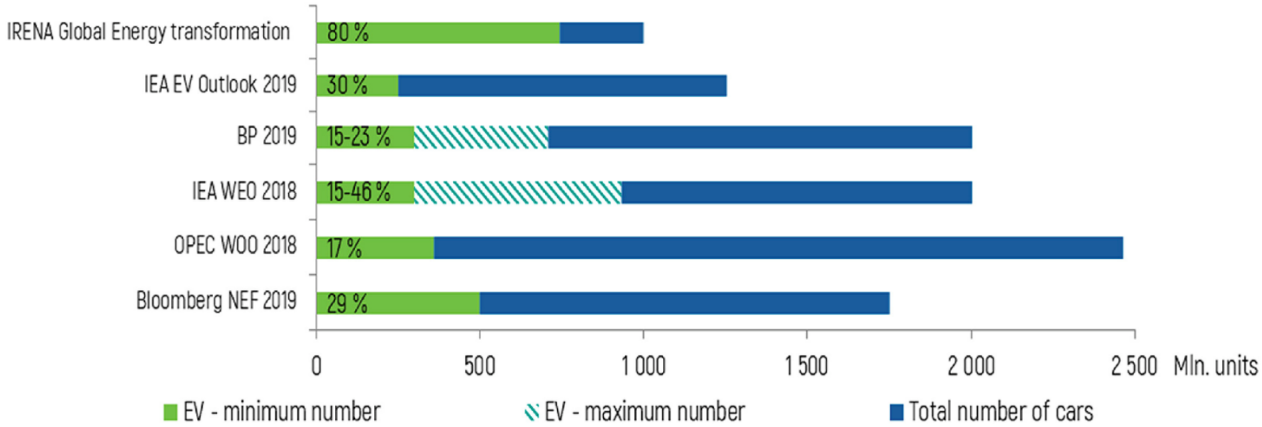


Figure 3-4 The number of EVs and their share in the global fleet in 2040

Modified from Kapustin & Grushevenko, 2020. IRENA represents for International Renewable Energy Agency. IEA WEO represents for International Energy Agency World Energy Outlook. OPEC WOO is the Organization of the Petroleum Exporting Countries World Oil Outlooks. Bloomberg NEF refers to Bloomberg Newe Energy Fiancee.

According to these estimates, I have developed the demand growth scenarios for this study. The basic vehicle stock number is obtained from total light-duty vehicle numbers for each region in 2030 from Annual Energy Outlook 2018. Assuming that vehicle stocks are the previous 15-year cumulative sales, I have designed the scenarios to reflect 12.5%, 25%, and 37.5% of the total stock of all light-duty vehicles to be battery EVs. These scenarios are far aggressive in EV adoptions than AEO 2018, which only forecasts less than 5 percent of national adoptions. However, the scenarios are feasible, within the range of the estimates shown in Figure 3-4, reflecting recent trends and forming a series of viable side cases worthy of examining.

Accordingly, the number of EVs are calculated for the three case study regions for each scenario, respectively. Note that the total number of vehicles estimated for SERC-S is the highest among the three (11.7 million vehicles compared to 8.9 million in Cal-ISO and 4.4 million in NYISO), showing a larger potential if the regions achieve a similar level of EV penetration.

Table 3-1 Summary of scenarios settings and associated EV stock forecasts

Scenario	Details	Equivalent Policy Example	Regional EV Stock Numbers in 2030 (Million)		
			SERC-S	NYISO	Cal-ISO
Ref	*AEO2018*		0.54	0.19	0.44
EV12.5	*12.5% of all vehicles are battery EV*	*EV sales mandate of 25% starting in 2023*	1.47	0.55	1.12
EV25	*25% of all vehicles are battery EV*	*EV sales mandate of 50% starting in 2023*	2.94	1.1	2.23
EV37.5	*37.5% of all vehicles are battery EV*	*EV sales mandate of 75% starting in 2023*	4.42	1.65	3.35

3.5.3 Electric vehicle charging curve

Many previous analyses (Choi et al., 2013; Al-Alawi & Bradley, 2013b; Galus et al., 2010; Liu et al., 2016) have developed EV charging profiles. The main merit of using these developed charging profiles is to produce comparable results with the previous EV studies. However, many of the simulations are based on generalizing national survey results, which are not specific to our research areas (Galus et al., 2010; Liu et al., 2016). Besides, the results may be outdated since many of the previous results leveraged the survey done before 2007, which requires updating to the recent behavior changes (Choi et al., 2013; Galus et al., 2010).

In comparison, this study leverages recent surveying results from National Household Travel Survey (NHTS) 2017, which provides both regionally specific and up-to-date data for deriving EV charging patterns. NHTS 2017, sponsored by the U.S. Department of Transportation (US DOT), provides detailed state-specific information about daily travel directly from a stratified random 129,112 sample of U. S. households(Garrett et al., 2019).

This survey results have several merits. Firstly, it combines and matches detailed travel, passenger, vehicle, household, and trip data. It collects daily trip data in terms of when and how the person travels and links these trips to the vehicle info database and the household information. This facilitates cross-referencing and filter functions from different aspects to examine the travel data. For example, NHTS helps us to identify specific trips done by electric vehicles by state, respectively. Secondly, NTHS 2017 covers add-on samples in Georgia, California, and New York State, which are the research areas that this study examines.

Table 3-2 NTHS 2017 data coverage and its focus states

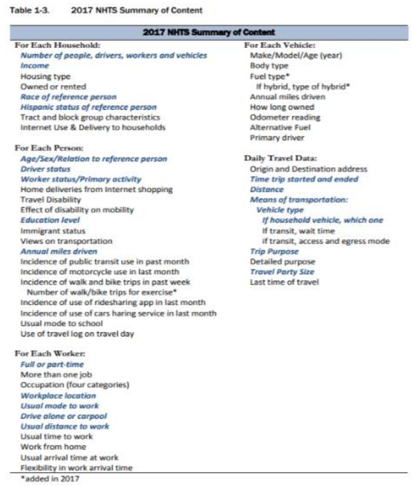


Table 1-3. 2017 NHTS Summary of Content

2017 NHTS Summary of Content

For Each Household:
Number of people, drivers, workers and vehicles
Income
Housing type
Owned or rented
Race of reference person
Hispanic status of reference person
Tract and block group characteristics
Internet Use & Delivery to households

For Each Person:
Age/Sex/Relation to reference person
Driver status
Worker status/Primary activity
Home deliveries from Internet shopping
Travel Disability
Effect of disability on mobility
Education level
Immigrant status
Views on transportation
Annual miles driven
Incidence of public transit use in past month
Incidence of motorcycle use in last month
Incidence of walk and bike trips in past week
Number of walk/bike trips for exercise*
Incidence of use of ridesharing app in last month
Incidence of use of cars haring service in last month
Usual mode to school
Use of travel log on travel day

For Each Worker:
Full or part-time
More than one job
Occupation (four categories)
Workplace location
Usual mode to work
Drive alone or carpool
Usual distance to work
Usual time to work
Work from home
Usual arrival time at work
Flexibility in work arrival time

For Each Vehicle:
Make/Model/Age (year)
Body type
Fuel type*
If hybrid, type of hybrid*
Annual miles driven
How long owned
Odometer reading
Alternative Fuel
Primary driver

Daily Travel Data:
Origin and Destination address
Time trip started and ended
Distance
Means of transportation:
Vehicle type
If household vehicle, which one
If transit, wait time
if transit, access and egress mode
Trip Purpose
Detailed purpose
Travel Party Size
Last time of travel

*added in 2017

Add-on Partner	Target Number of Completed Households[1]
Arizona	2,444
California	24,000
Georgia	8,000
Maryland	1,000
New York State	15,851
North Carolina	8,000
South Carolina	6,500
Texas	20,000
Wisconsin	11,000

[1] These are households for which all of the household members ages five and older complete the retrieval survey.

Source: U.S. Department of Transportation, Federal Highway Administration, 2017 National Household Travel Survey. URL: http://nhts.ornl.gov.

Similar to (Choi et al., 2013), several assumptions are made about the charging pattern for uncontrolled charging - the vehicle begins charging upon completion of the last journey of the day and charges at a given uniform rate until all energy used during the day has been restored. Furthermore, to calculate the charging profile, we further need to introduce more assumptions about charging rate and vehicle efficiency. We use IEA EV Outlook 2019 (https://www.iea.org/reports/global-ev-outlook-2019) for reference to assume that:

- The efficiency for driving is 0.23 kWh/km (0.37 kWh/mile)

- The charging power is 8 kW
- Charging losses are 5%

Following this method, the EV charging loads are constructed for the three regions, reflecting how much residents rely on their personal vehicles to travel. In addition, the distribution of the charging behavior within a day is different. California and New York have similar peak hours at 6 to 7 p.m., while in SERC-S, the peak of charging is later at 8 to 9 p.m.

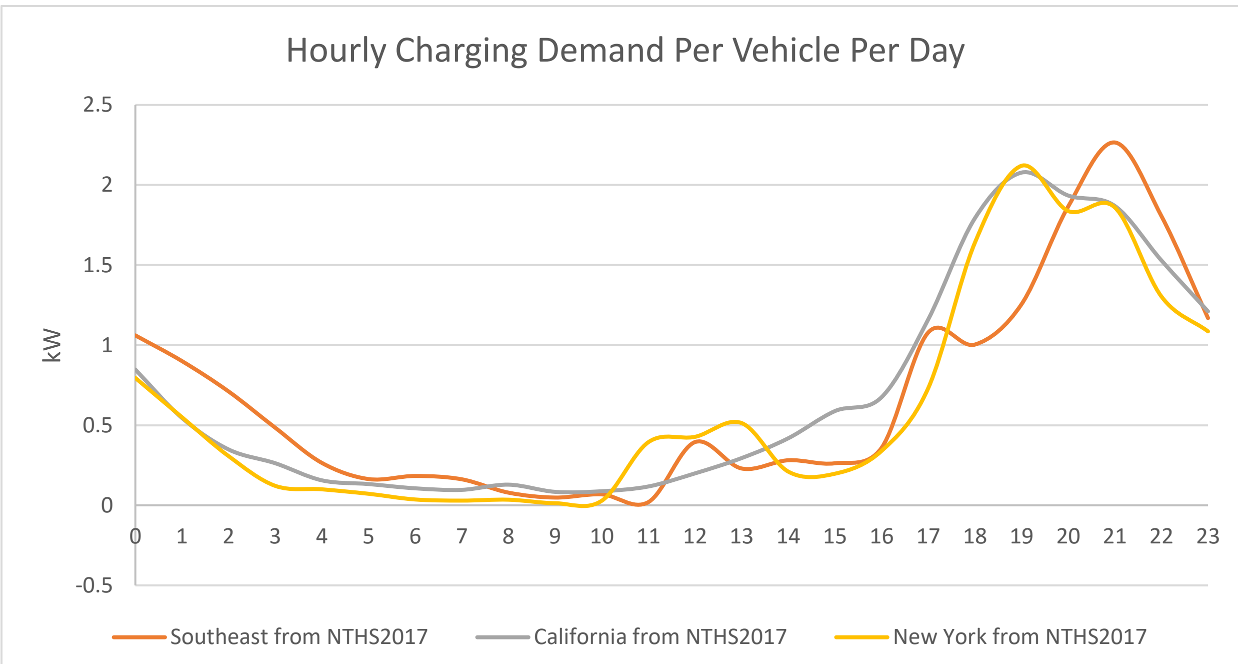


Figure 3-5 Electric vehicle hourly charging demand

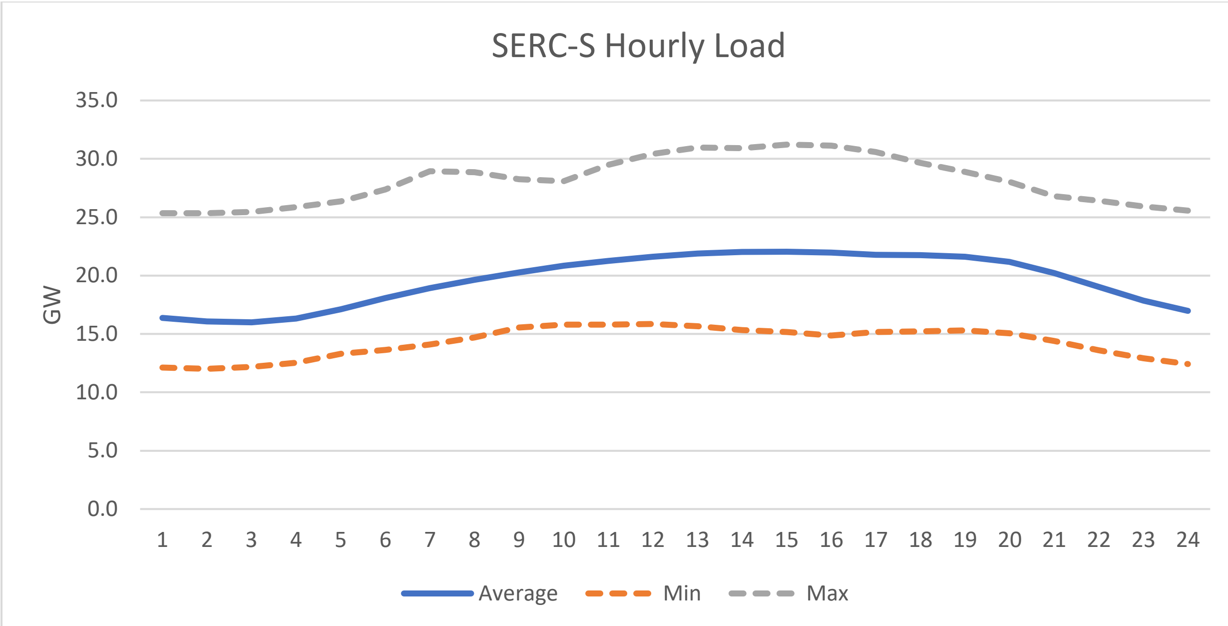
3.5.4 Regional power grid dispatch model

In the previous section, the EV demands have been identified. Correspondingly, in this section, the information on the grid practice of the three regions is examined. Specifically, the demand curves and the supply curves are derived for the three regions, respectively.

3.5.4.1 Regional Demand Forecasts

Firstly, the historical demand is examined. The SNL database provides hourly info on the demands for the three areas. The load curves are identified in this study using the 2017 and 2018 hourly averages. Since during different hours of the day, the electricity demand may vary differently. The minimum, average, and maximum loads are recorded to be further used for deriving the minimum, average, and maximum demand load scenarios for further sensitivity analysis. The scenario using average hourly demand is noted as the "Average_Demand" scenario. The two side cases are noted as "Low_Demand" and "High_Demand," reflecting the hourly minimum and maximum hourly demands, respectively (Figure 3-6). These scenarios are further examined and compared in Section 3.6.3.

In general, the load curves show regional disparities. SERC-S has the peak of demand at about 2 p.m., which is not similar to NYISO or Cal-ISO peak hour, which often lies in the early evening, between 6 p.m. to 7 p.m. in the early evening.



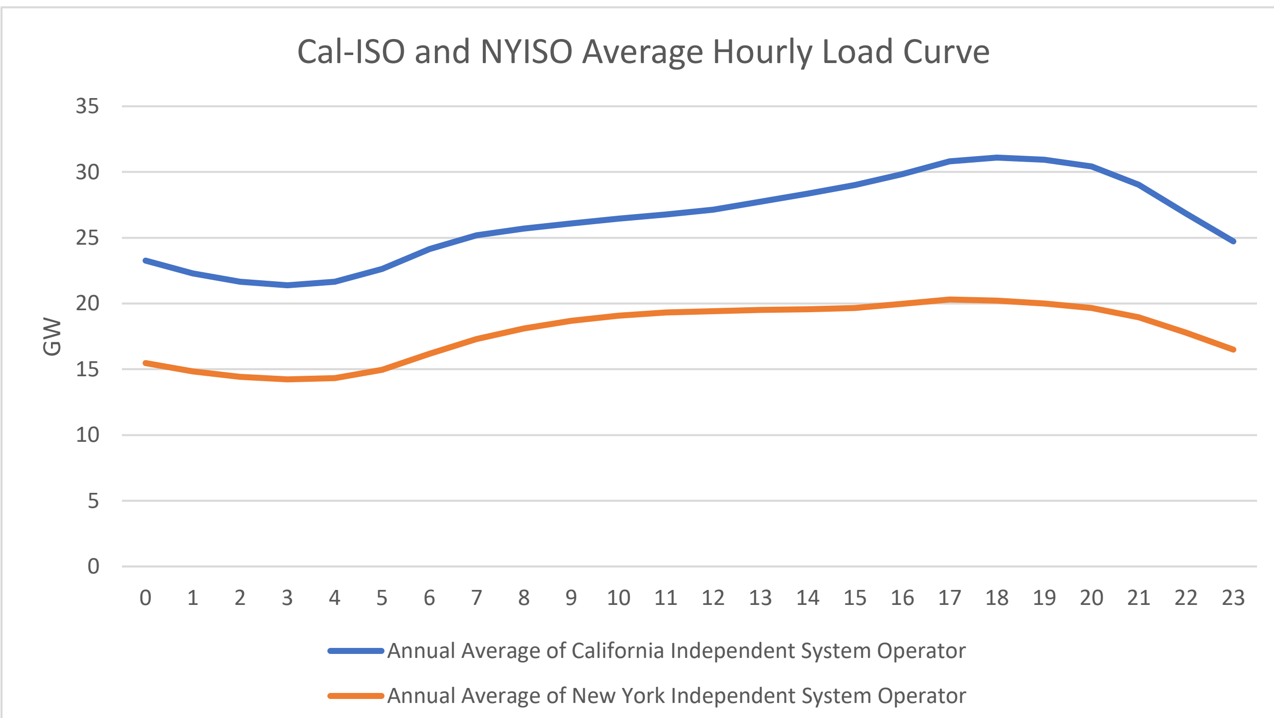


Figure 3-6 Annual hourly load summary for Southeast (above), Cal-ISO, and NYISO (below)

Source: SNL subscriptions

Based on these estimates, the EV charging demands under three scenarios are integrated to reflect the scenario total load curves. The extra EV vehicle numbers are calculated by the forecasts in each of the three EV scenarios minus the number of EVs already considered in the reference scenario. Afterward, the estimates are multiplied by the hourly load shown in the daily charging curve to derive the additional EV demand at each hour.

The results of regional EV loads show that combining the EV load, the estimated load is about 3.1%, 1.1%, 1.5% in all the regions for EV12.5 as to the total load. For NYISO, the percentage is lower since there are fewer vehicles and less driving per vehicle indicated before. However, in SERC-S, the EV demands can be a very significant part of the total grid load – in EV37.5 case, the extra demand from EV charging can be11.7% of the total loads.

Table 3-3 Regional EV extra loads for each scenario

		EV12.5	EV25	EV37.5
SERC-S	**Annual Extra Demand (Thousand GWh)**	5.5	14.1	22.7
	% / Total Grid Load	3.1%	7.6%	11.7%
NYISO	**Annual Extra Demand (Thousand GWh)**	1.9	4.9	7.9
	% / Total Grid Load	1.1%	2.7%	4.3%
Cal-ISO	**Annual Extra Demand (Thousand GWh)**	4.1	10.9	17.7
	% / Total Grid Load	1.5%	3.9%	6.2%

Furthermore, it’s also worthwhile to examine the combination of the hourly load and the EV charging daily profile. Since the cost of the day for marginal electricity generation can be vastly different given different generation resources and technology, the matching of the load hourly curves can influence the costs of the electricity generation significantly.

The profile shows that the EV will not add so much to the afternoon peak of the power grid but adds some difficulties in the later afternoon, which is considered to be evening after-peak load time. This percentage of demand additions compared to the cost additions is further examined in the latter section when the costs per load are estimated.

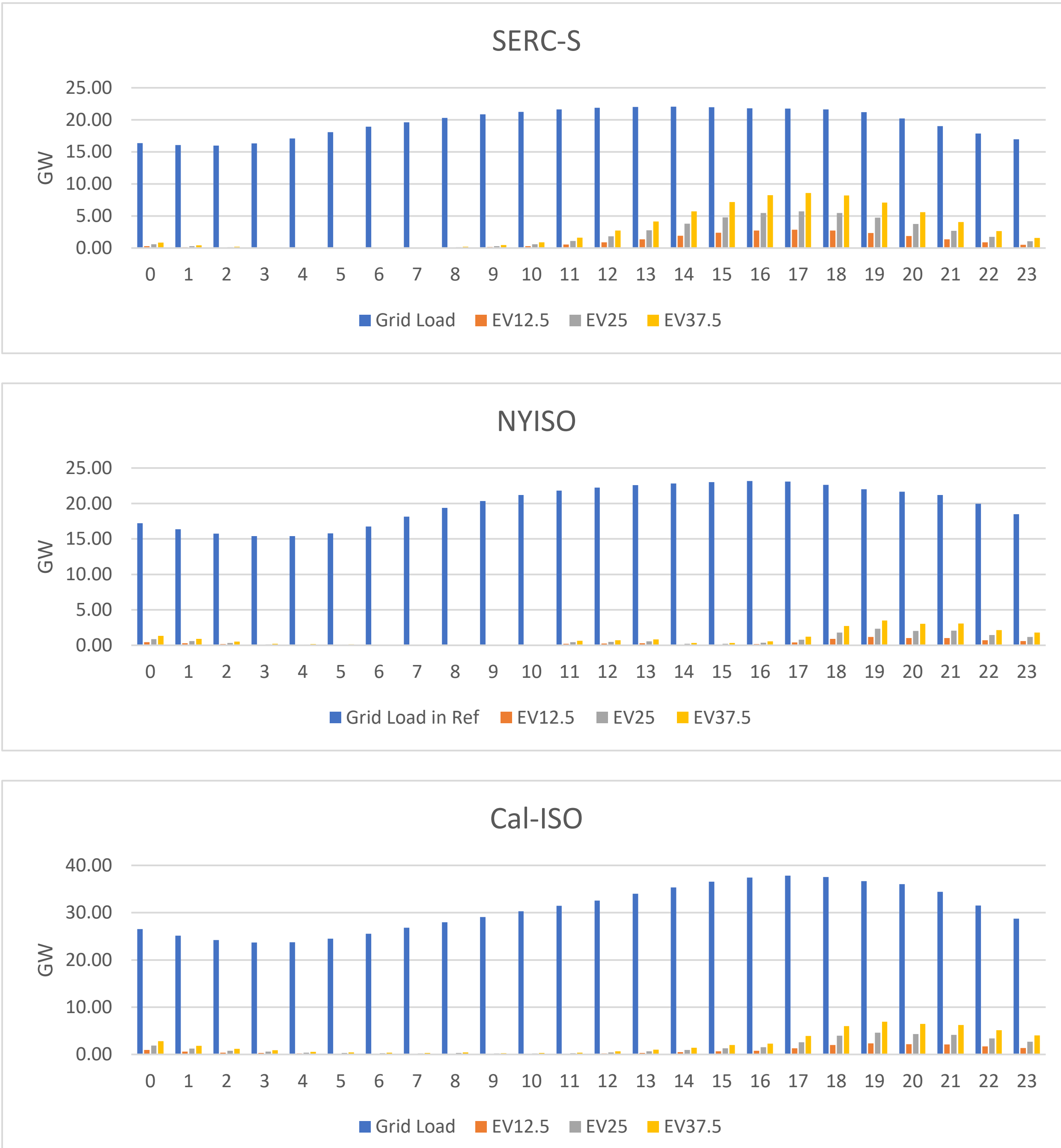


Figure 3-7 Daily loads in Ref and additional EV charging loads for three regions

3.5.4.2 Supply Curve

Another component of the power grid is the supply curve. The supply curves in our study are O&M-based curves with time slice-specific resources availability adjustments. Specifically, the supply curves describe the generation capacity available at specific time slices ranked by its O&M costs. Unlike most previous studies to reply heavily on historical generation capacity to simulate the future supply curve, such as Mohamed, 2019; Jiang 2017; Ma et al., 2012; Al-Alawi & Bradley, 2013b; Buekers et al., 2014; Choi et al., 2013, my study adopts the forecasts of the generation resources available in 2030 from GT-NEMS projections. One of the merits of this approach is that the forecasts weigh more future capacity changes into considerations, aiming to provide more realistic estimates of the future status of the electric power sectors.

The study aligns with the GT-NEMS 2018 Reference scenario to divide the overall time into 9 different time slices – three seasons indicator coupled with three load types - the seasons are 1-winter, 2-summer, 3-spring/fall. Within a season, the time slices 1 to 3 are sorted by peak (highest 1% of demands), intermediate or shoulder (next 49% of demands), and base or off-peak (lowest 50% of demands). The time slice differentiations reflect the practice of power system operations, showing differences between resource availability (Figure 3-8) and associated costs. For example, Cal-ISO relies substantially more on solar generation in fall/spring peak than the same season offpeak hours and peak hour in winter. At each time slice, the regional generation resources and corresponding marginal costs are forecasted in the year 2030.

GT-NEMS provides detailed resource planning for each time slice at each region. Examining the results of the three regions show significant regional heterogeneity in resource availability at different time slices. Even though the fact that natural gas combined cycle (NGCC) generation is projected to play a big part in all three regions, the reliance on NGCC is different among the three regions. NGCC is projected to be about 28% and 24% for Cal-ISO and NY-ISO, respectively. However, Southeast mostly relies on NGCC for peak hour (about 8% average across all seasons) and at other time slices, the NGCC only accounts for about 1% of the total generation capacity available. Instead, SERC-S is projected to rely on coal for more than 40% of its generation regardless of the time slices in 2030. Comparatively, NY-ISO has a strong reliance on nuclear and natural gas/oil turbines. Cal-ISO is coal-free in 2030 but still relies on renewable resources, including solar, wind, hydro, and geothermal.

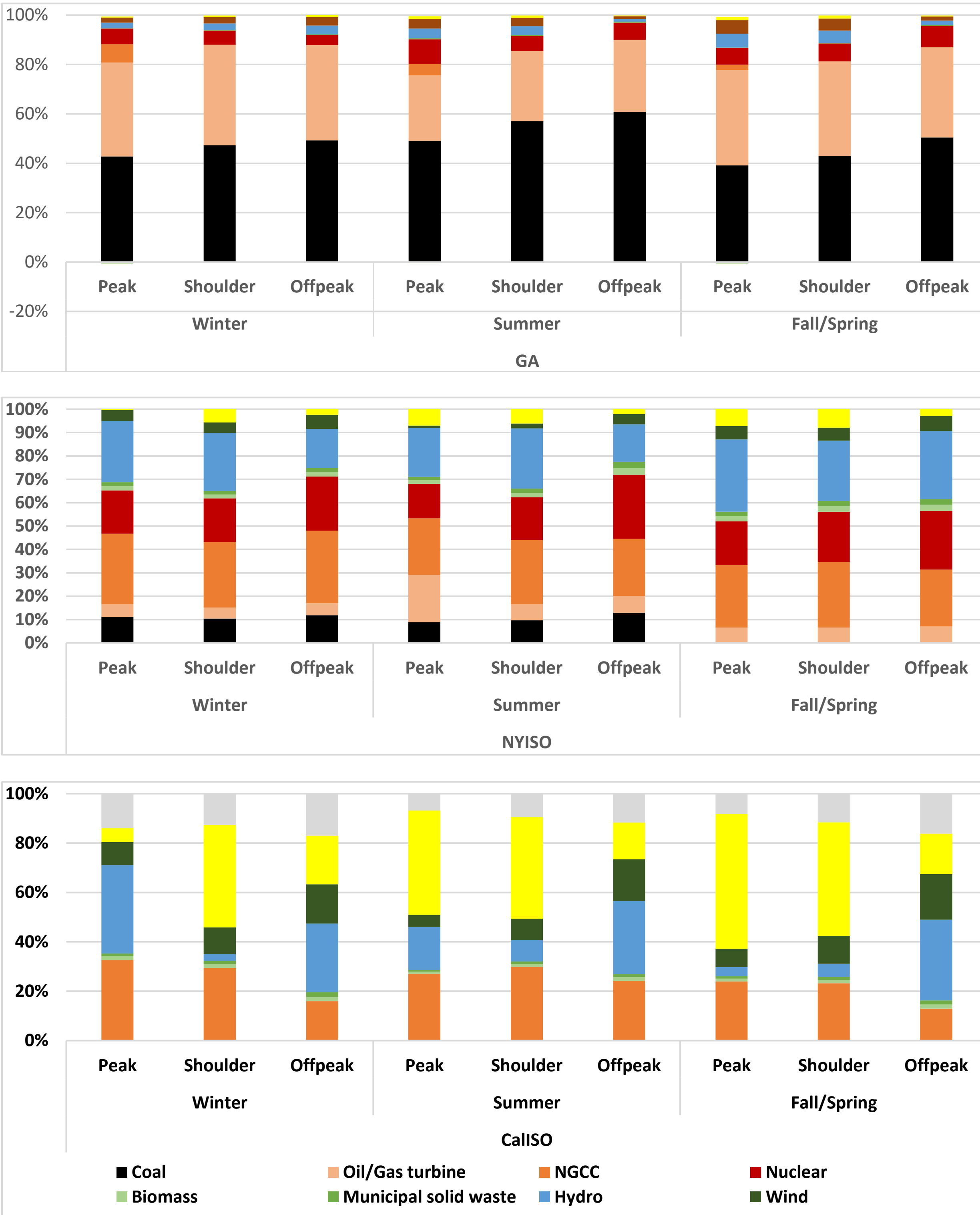


Figure 3-8 Resource availability for the 9 time-slices for three regions

Based on the resource availability at different time slices, the supply curves are constructed by ranking the O&M costs from lowest to highest. You can find all supply curves for all regions and all-time slices in the appendix of this chapter. To illustrate the process, the summer supply curves at SERC-S for summer are showed as an example. The Y-axis describes the O&M costs per generation for the generation units. After ranking from the lowest to highest, the available cumulative capacity is the x-axis on each curve. And on the curve, the dots represent a generation unit possible at this time slice.

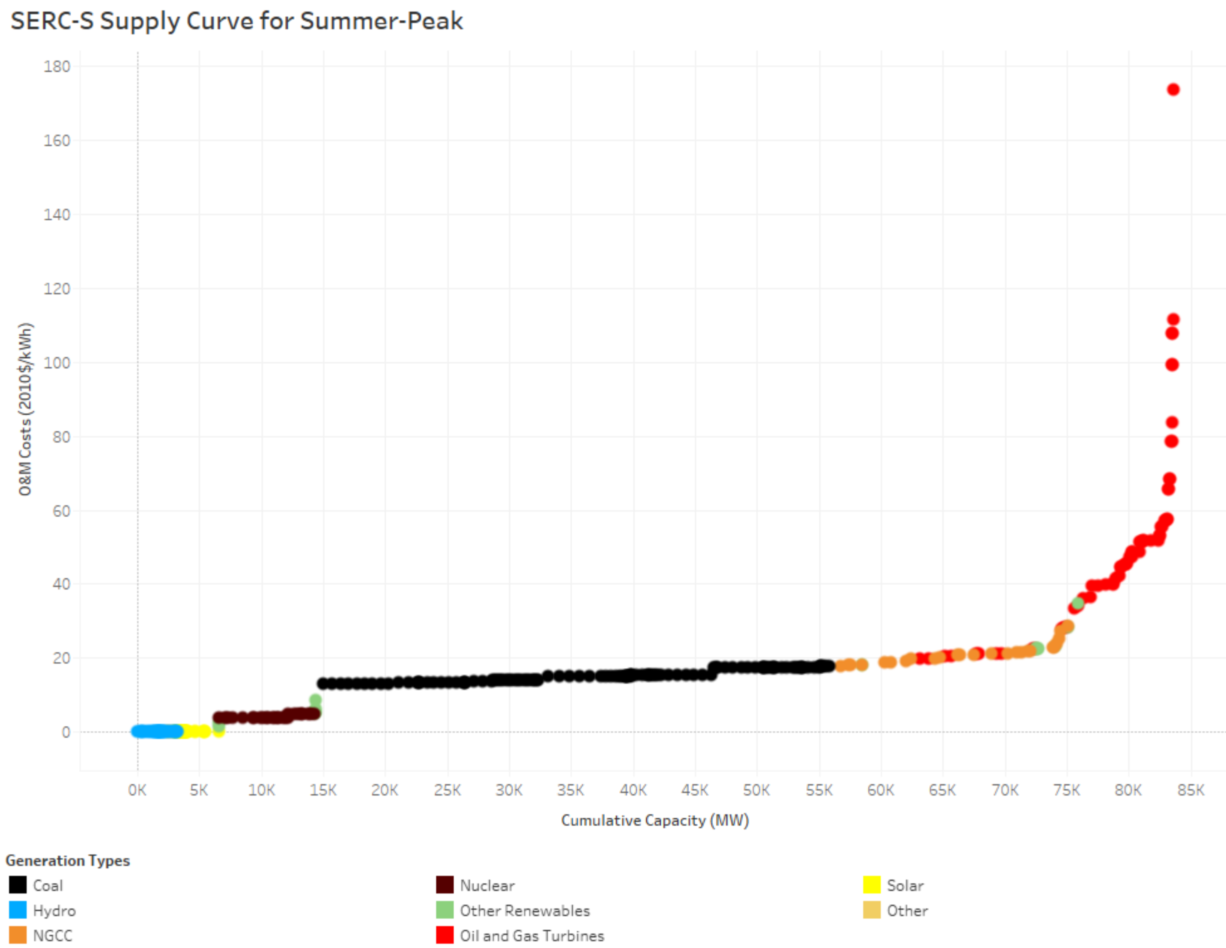


Figure 3-9 Supply curve for the Southeast summer peak hour

The curves have described the order of resource allocation for power generation. In general, intermediate renewable resources and nuclear are picked first because of their low close-to-zero O&M costs. However, limited to its availability, the size of the intermediate renewable resources varies in different time slices. Coal and natural gas combined cycle (NGCC) plants are usually the next resources to pick because of their low O&M costs. Oil and gas turbines usually are the last resources for the grid and are much largely used in peak hours than off-peak and intermediate hours.

3.5.5 Integrations of EV demand and power grid management

This section explores the final results from the integration of the dispatch model matching with the regional demand, including EV charging loads and the regional supply of electricity. In other words, the results examine how the demand from EV charging can be met with the power grid resources. In this section, the overall cost impacts are summarized, along with the fuel portfolio impacts from EV adoption scenarios. Besides, the influences on carbon emission are also illustrated.

3.5.5.1 <u>Additional generation resources</u>

With the supply curves available, adding the EV load to the existing demand shows what the resources used to satisfy the needs of EV demand are. Because the demands fluctuate, the average hourly demand is used for the regions, respectively. The results of the additional resources used are summarized. In SERC-S, about 20% of the EV additional loads are still met by the generation from the coal, making it the only region that still relies on coal to supply the EV charging demands. NGCC gradually increases its use from 3% to 6% and 13% as EV adoptions increase for SERC-S. Cal-ISO also sees an increasing trend of NGCC usage if EV penetration increases. The rest of the demands are met by combustion turbines. However, in NY-ISO, the model anticipates 100% of the load being satisfied by combustion turbines.

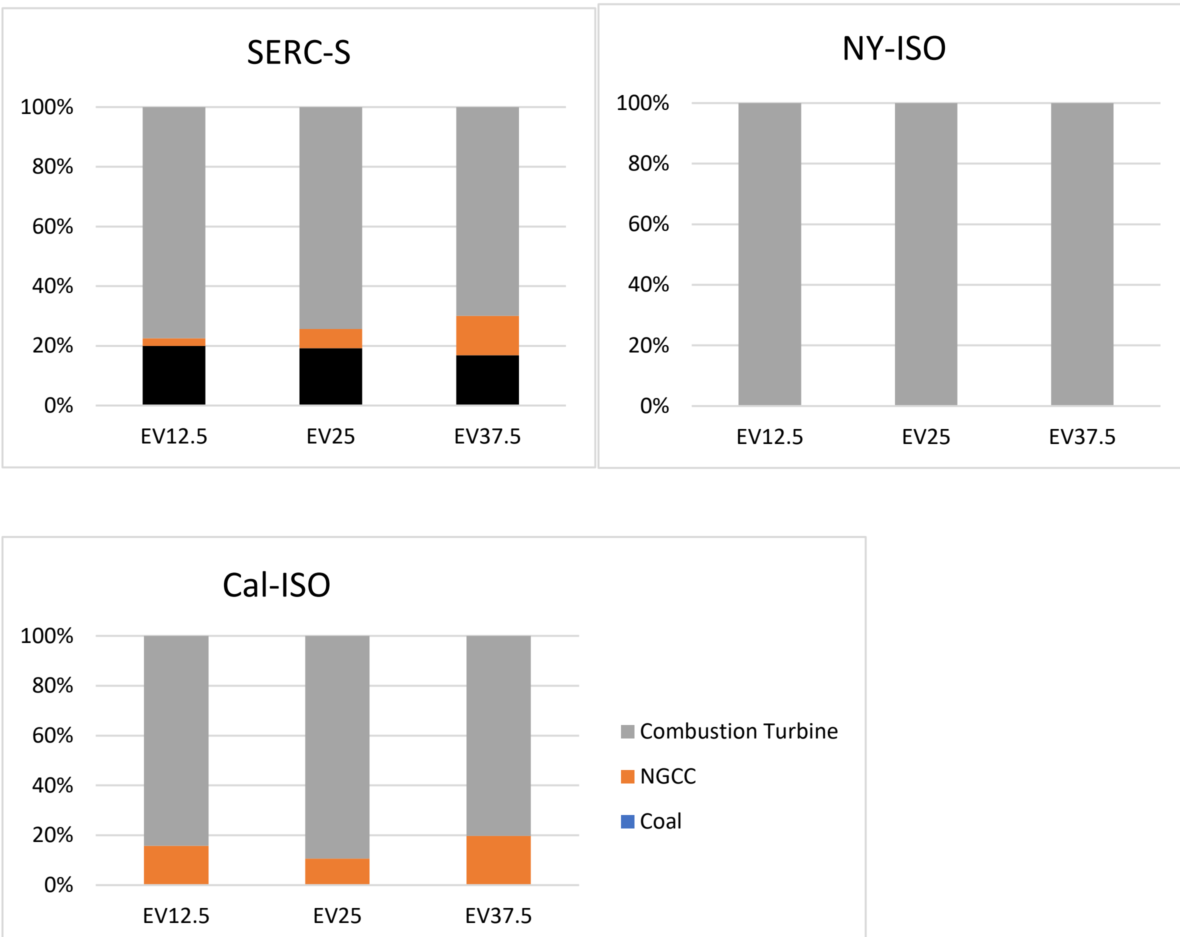


Figure 3-10 Generation resources serving EV Demands

3.5.5.2 <u>Costs on electricity power sector and emission impacts</u>

Using the integrated dispatch model constructed, the additional costs of the grid satisfying the EV demands are explored. In general, the EV charging demands increased the hourly O&M costs. By the nature of the electricity operations and the uneven distributions of the EV demands within a day, the increases are significant time-sensitive - when adding the EV charging loads to the existing demand, both the timing of the charging and the distribution of the matter of the existing demand. Moving along the supply curve to accommodate higher demand, the marginal costs increase, especially at peak hours. Thus, the costs would be significantly higher when the EV charging behaviors coincide with the peak of the existing loads and vice versa.

Among the three regions, SERC-S has the lowest magnitude of percentage increase in the hourly costs, due to relatively higher generation resources availability and departure of the existing demand peak, about 2 or 3 p.m., from the EV charging peaks, estimated at 8 to 9 p.m. The overall hourly costs increase modest – averaging 9.3%, 19.4%, and 30.0% for the scenarios of EV12.5, EV25, and EV37.5, respectively. Unlike SERC-S, for NYISO, the charging demands increase the hourly costs dramatically at 9 to 11 p.m. – the costs increase about 8.3 times of its original costs in the EV37.5 scenario. Similar to Cal-ISO, the time between 8 and 11 p.m. sees a dramatic increase from EV charging demand. The effect is mostly due to the coinciding of the charging peak and existing demand peaks. Thus, the grid sees a dramatic pressure to supply the electricity to satisfy the needs. When the power sector moves to its very last resources, usually gas and oil turbines, the marginal costs increase dramatically, as shown from the "sticky bar" supply curves. However, unlike NYISO, the Cal-ISO also has a higher percentage increase at midnight time (between 0 a.m. to 4 a.m.) mostly due to lack of resource availability when the grid has adopted the intermittent renewable resources, which generates less during these hours.

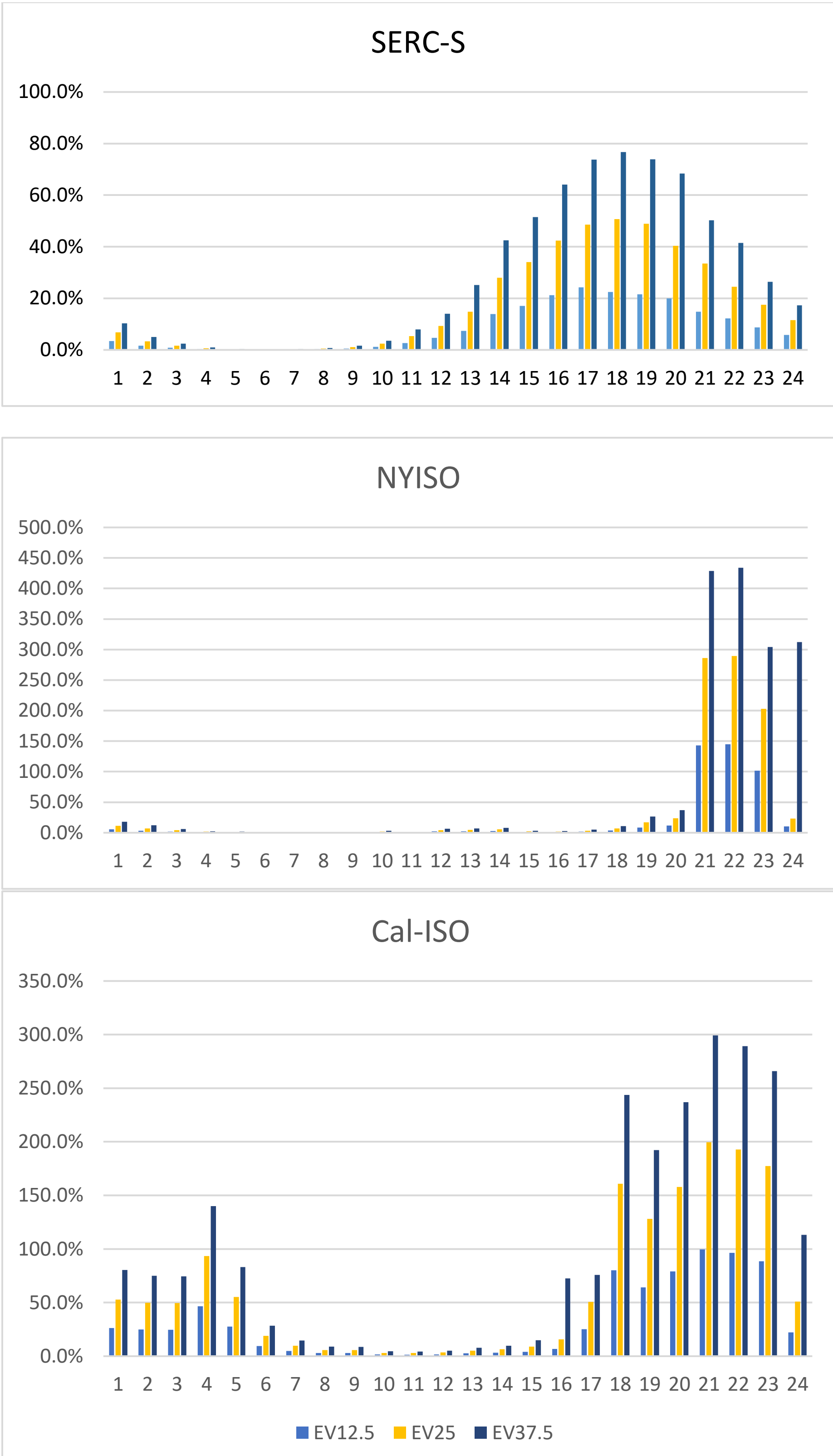


Figure 3-11 Percent increases in hourly load due to EV loads compared to the Reference scenario

Aggregating the hourly load leads to a summary of total costs to serve the EV loads. The exact costs vary across the regions ranging from 148.4 million per year for SERC-S in the EV12.5 scenario to about 1.4 billion per year for NYISO in the EV37.5 scenario. Since the total loads of EV charging for each scenario and each region are different, the more comparable measurement is the cost per generation. For SERC-S, the marginal costs for generation are forecasted to be 1.73, 1.78, and 1.87 cents/kWh, respectively, which are the lowest among the three regions. Cal-ISO has comparable higher marginal costs around 8 cents/kWh while NYISO has the highest marginal costs per generation for the EV, charging around 13.6 cents/kWh, 13.7 cents/kWh, and 16.10 cents/kWh for the three scenarios, respectively. The differences in the O&M costs due to the EV charging loads coincide with the resources allocated to generate the electricity. Since SERC-S leverages its coal plants and NGCC plants to serve the extra loads, the O&M costs are relatively low. On the contrary, to deal with the additional loads, NYISO has to use the oil and gas combustion turbines, which are very high in marginal generation costs.

Table 3-4 Additional O&M costs serving the EV demands

		EV12.5	**EV25**	**EV37.5**
Southeast	million $	148.44	305.51	483.57
	cent/kWh	1.73	1.78	1.87
NYISO	million $	405.12	812.58	1433.22
	cent/kWh	13.65	13.69	16.10
Cal-ISO	million $	550.21	1129.16	1129.16
	cent/kWh	8.11	8.32	8.32

Notes: the costs are estimated under the average load daily curve estimates.

Other than additional costs, the EV charging loads also emit extra carbon dioxide when the electricity is generated. However, since the EVs are replacing gasoline vehicles and can be seen as carbon-free at usage, the carbon dioxide calculation includes the avoided gasoline carbon emissions. To provide accurate and reliable estimates, I have applied the AEO 2018's average emission factor in 2030 into the analysis to do the calculation, which assumes 1.01, 0.42 and 0.57 metric ton of CO_2 emissions per MWh respectively for coal combined cycle, natural gas combined cycle and combustion turbines, respectively. In addition, to calculate the avoided gasline usage and emissions, this study adopts AEO 2018 projected national average MPG for gasoline vehicle stock in 2030, 29.74 miles/gallon. The consumptions are calculated using NHTS 2017, showing 41.56, 45.04, and 39.87 vehicle-mile-travel (VMT) per day for SERC-S, NY-ISO and Cal-ISO, respectively. The emission factor is obtained from US EPA (US EPA, 2018c), which shows an emission factor of 8.8 kg/gallon used for traditional gasoline vehicles.

The aggregate results of carbon emissions show all three regions and all scenarios reduce CO_2 emissions. In general, in the EV12.5 scenario, the extra carbon dioxide emission from EV charging is smaller than that of avoided gasoline usage. And in the EV37.5 scenario, with the most aggressive adoptions of EVs, the CO_2 emission generated by the electric power sector and avoided from gasoline usage are both larger, but the net impacts are still reducing overall carbon dioxide emissions.

However, the results also show regional heterogeneities. Among the three regions, SERC-S has the largest net reductions in carbon dioxide emissions, 2.66 million metric tons, 5.48 million metric tons, and 8.74 million metric tons in the year 2030 for the three EV adoption scenarios, respectively. The main factor that contributes to SERC-S's large reductions is the total volume of total traveling needs, which means the largest potentials for avoiding carbon dioxide emissions from traditional internal combustion engines. However, because of its generation reliance on coal to support the generation, the carbon emissions from power generation are the largest among the three regions – 5.6, 11.1, and 16.1 million metric tons of carbon dioxide per year for the three scenarios, respectively.

By comparison, Cal-ISO has relatively larger vehicle stocks, thus a larger emission reduction from the avoided gasoline than NY-ISO. In addition, because of its reliance on NGCC, the total emissions from the power generation are relatively smaller than SERC-S. The net carbon emissions for Cal-ISO are 2.76, 5.62, and 8.30 million metric tons for the three scenarios, respectively. In terms of the total mileage of traveling projected for EVs, NY-ISO is the smallest among the three regions. Thus the emission reduction benefits are smaller in size – ranging from 1.16 million metric tons in the EV12.5 scenario to 3.48 million metric tons per year in the EV37.5 scenario.

Table 3-5 Carbon dioxide emission impacts for all regions and all EV penetration scenarios

Units: MMst per year	**SERC-S**			**NYISO**			**Cal-ISO**		
	EV12.5	**EV25**	**EV37.5**	**EV12.5**	**EV25**	**EV37.5**	**EV12.5**	**EV25**	**EV37.5**
Coal	1.72	3.31	4.37	0.00	0.00	0.00	0.00	0.00	0.00
NGCC	0.09	0.46	1.42	0.00	0.00	0.00	0.30	0.84	0.92
Combustion Turbine	3.82	7.34	10.35	1.70	3.41	5.11	3.49	6.63	10.42
Subtotal	5.63	11.11	16.14	1.70	3.41	5.11	3.78	7.47	11.34
Avoided Gasoline Emissions	-8.29	-16.59	-24.88	-2.86	-5.73	-8.59	-6.54	-13.09	-19.63
Net Impacts	-2.66	-5.48	-8.74	-1.16	-2.32	-3.48	-2.76	-5.62	-8.30

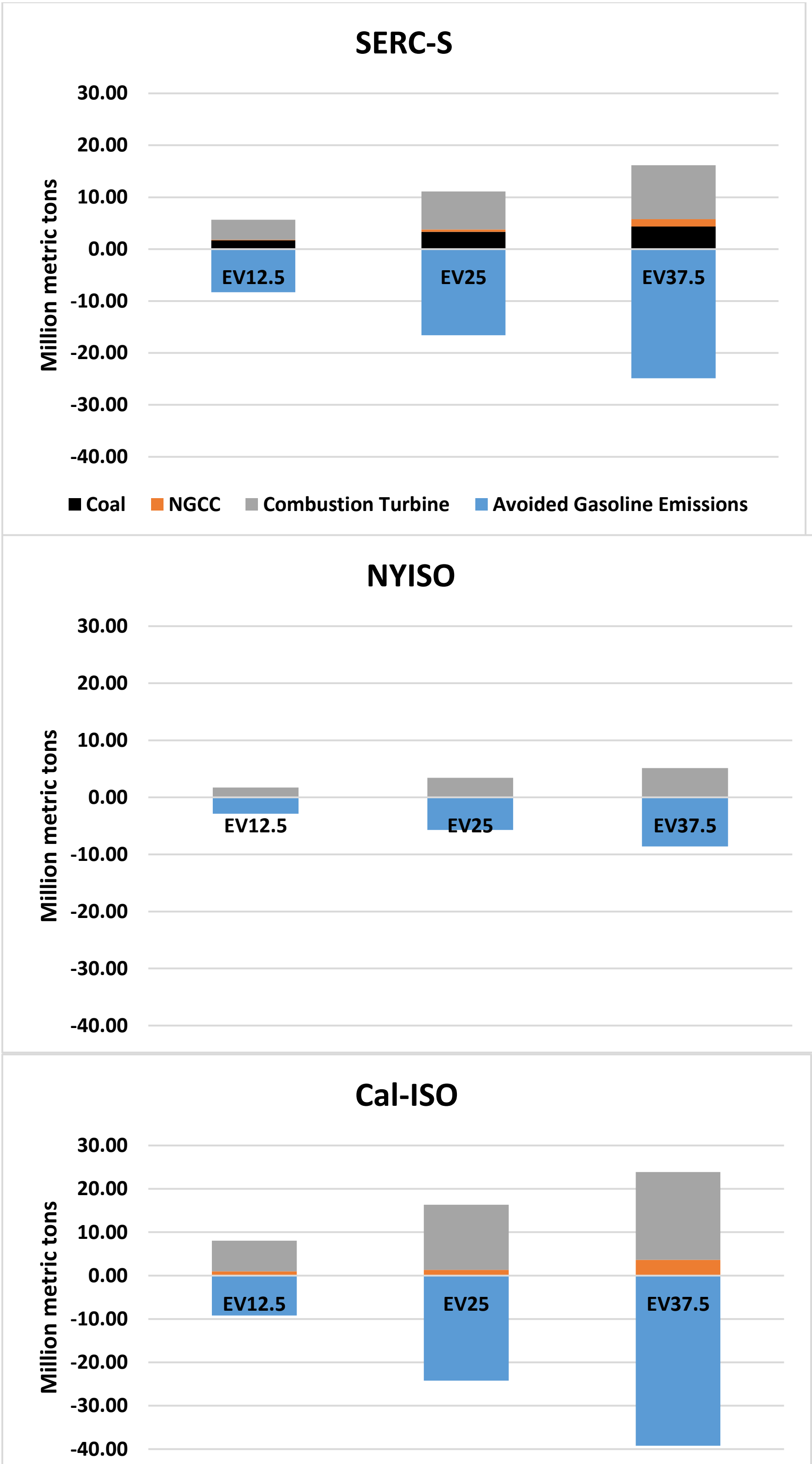


Figure 3-12 Induced carbon dioxide emissions changes for all regions and scenarios

3.6 Discussions and policy implications

3.6.1 Conclusions

In this study, I have examined, without new capacity planning and coordinated charging, in the short term, how the electric power 'passively' serves the additional demand from the electric vehicles as additional loads. This study has used recently available regional-specific traveling data coupled with cutting-edge grid operational forecasts to reflect the reality of the future.

Table 3.6 Summary table of the conclusions by regions and scenarios

	SERC-S			**NYISO**			**Cal-ISO**		
	EV12.5	**EV25**	**EV37.5**	**EV12.5**	**EV25**	**EV37.5**	**EV12.5**	**EV25**	**EV37.5**
% increase of demand	3.1%	7.6%	11.7%	1.1%	2.7%	4.3%	1.5%	3.9%	6.2%
additional O&M cost (million $)	148.44	305.51	483.57	405.12	812.58	1433.22	550.21	1129.16	1129.16
% increase the total operational costs	8.8%	18.1%	28.6%	24.2%	48.5%	85.5%	36.8%	74.1%	116.6%
average additional O&M cost (cent/kWh)	1.73	1.78	1.87	13.65	13.69	16.10	8.11	8.32	8.32
CO_2 reduced (MMmt)	2.66	5.48	8.74	1.16	2.32	3.48	2.76	5.62	8.30
Additional variable costs per CO_2 reduction ($/metric tons of CO_2)	55.82	55.78	55.31	349.24	350.25	411.84	199.35	200.92	136.04

Overall, some similarities are found across all regions. The increases in demands due to EV charging needs are substantial, especially for the EV37.5 scenario. The demands for EV charging can be as high as 11.7% of the total loads in the SERC-S EV37.5 scenario. Correspondingly, the O&M costs increase but disproportional larger compared to the increase of demands. Even in SERC-S, where the average additional O&M costs are the lowest, the increase in operational costs is relatively large – 8.8%, 18.1%, and 28.6% for all scenarios, respectively, more than 2 times the percentage increases in demands.

Besides, the results also show a significant level of carbon emission reductions – mostly due to the avoided gasoline usage. As the EV adoptions get larger, the volumes of the reduced CO_2 are larger. For example, in SERC-S, the CO_2 emission reduction per year is 2.66 million metric tons, 5.48 million metric tons, and 8.74 million metric tons per for the three EV scenarios, respectively.

However, the results reveal more regional heterogeneities. Among the three regions, SERC-S has the largest volume of EV charging loads but has the lowest additional costs increased per generation, resulting from the detachment of the demand peak and the EV charging peak, and the relatively better generation resource availability of the coal and natural gas combined cycles compared to the other regions. Thus, the additional costs are as low as 1.73 cents/kWh, 1.78 cents/kWh, and 1.87 cents/kWh for the three EV scenarios, and the costs are relatively similar with the EV penetration get larger. By comparison, even with the smallest demands from EV charging, NY-ISO has higher operational cost additions due to its lack of cheap resources other than combustion turbines to serve the needs of EV charging. The additional costs for the three EV charging scenarios are larger than SERC-S, and the costs increase with more EV charging needs – 13.6 cents, 13.7 cents, and 16.1 cents per kWh in 2030. Like NYISO, the Cal-ISO region has no coal to serve the needs of the EV charging but uses substantial NGCC for electricity generation. As a result, for Cal-ISO, the cost additions are similar across all three EV scenarios and smaller than NYISO but larger than SERC-S estimates – ranging from 8.1 cents to 8.3 cents per kWh.

The CO_2 emission impacts also show regional differences. SERC-S has the largest CO_2 emission reductions, 8.74 million metric tons in the EV37.5 scenario due to the greatest EV demands. However, in the other two scenarios, the total volumes of the CO_2 emissions are lower than Cal-ISO since SERC-S uses coal for electricity generation. Benefiting from the relatively high demands and NGCC plants for generation, Cal-ISO reduces the largest amounts of CO_2 emissions 2.76 million metric tons in the EV12.5 scenario and 5.6 million metric tons in EV25. Due to its relatively smaller needs from EV and high reliance on the less efficient combustion turbines compared to NGCC plants, NYISO has the smallest amount of CO_2 emission reduced – 1.16 million metric tons, 2.32 million metric tons, and 3.48 metric tons per year.

Combing the information of the cost additions and CO_2 emission reductions, the three regions are projected to have a considerable additional cost per carbon reduction. SERC-S has the lowest estimates of about 55 $/metric ton of CO_2 abatement across all scenarios. However, for NYISO, due to its high cost and low abatements, the costs for CO_2 abatement are relatively high 349.2 $/metric tons, 350.3 $/metric tons, and 411.8$/metric ton per CO_2 reduced. Compared to the other two regions, Cal-ISO has modest costs for the carbon reductions - 199.4 $/metric ton, 200.9 $/metric ton, and 136.0 $/metric ton per CO_2 reduced.

3.6.2 Policy implications

The study has conducted case studies into three distinct regions, which differ in generation resources, power market dynamics, and EV charging portfolios. Thus, summarizing and comparing the results, several important policy implications are revealed.

First, this study shows due to the complexities of power generation practices, the EV promotion policies, such as EV sales mandates, may not harvest the desired purpose. The design of the EV-related policies, especially its policy evaluations, requires holistic views combining the power sector, the EV drivers, and other stakeholders into considerations. Estimating the policy impacts requires systematic modeling, often resulting in non-linear results over the stimulus. For example, using the grid average CO_2 emission intensity to calculate the marginal EV charging demands will significantly bias the reality.

In addition, this study also shows substantial additional operational and maintenance costs compared to the scenarios without EV adoptions. The EV charging can indeed bring extra demand, thus extra sources of income for electric power sectors, but the modeling results have revealed a substantially higher percentage of the additions on O&M costs. Without adjusting the generation units or coordinated charging behaviors, the electric power sector may face pressure to operate at a low total operational cost. However, the study does not take fixed O&M or levelized capacity costs into consideration, thus hard to compare to the long-term studies, such as Choi et al. 2013. Thus, the increases in additional O&M costs may not necessarily lead to higher average costs of electricities.

Besides, the analysis shows that the EV charging demands may be generated using carbon-intensive resources or relatively low efficient technology, such as coal combined cycle or the oil and gas turbines, leading to increases on average CO_2 intensity of the grid. It shows without coordination or capacity planning, the EV penetration not only puts pressure on grid operations by increasing operational costs but also casts difficulties for the power sector to achieve the goals of carbon emission reductions.

However, considering the emission avoided from gasoline usage, the overall impacts of the EV penetration are all positive. The policy implication is clear to support that promoting EV penetration, even under current gird operational practice, can be helpful to reduce the overall CO_2 emissions. But the costs of achieving the carbon reduction goals may vary – for example, NYISO may have as high as 411.8 \$/metric tons of CO_2 reduction. Those estimates provide information to design proper carbon emission plans, comparing and engaging various carbon emission reduction channels available.

Furthermore, the regional results confirm that regional heterogeneities exist. We have seen the calls in the policy arena for universal EV mandates across all states, such as the Green New Deal. Such national policies help to avoid policy leakages and signal positive changes to the industries. However, facing similar policy stimulus, the regional situations, including the current demands, the volume of the EV stocks, and driving patterns, trigger different regional outcomes. For example, facing similar EV penetration, SERC-S is the only region among the three that has the cost per CO_2 abatement of around 55 \$/metric tons of CO_2, which is close to the social cost of carbon identified by the US EPA. In comparison, NYISO faces the highest carbon emission reduction costs, and the costs also escalate with the level of the desired EV penetration. These cost escalation effects do not exist in SERC-S or Cal-ISO.

The differences in the regional policy outcomes revealed by the regional heterogeneities indicate some potential equity issues when different regions face a similar level of EV penetration mandates from a higher level of the government, for example, the state coalitions or the federal. Across different regions, both the costs and the effects of carbon emission reductions can be different. Thus equity issues may arise if universal legislation or regulation are made and thus distribute different burdens and benefits among the regions. This study has confirmed that the existence of the equity concerns, calling for scrutiny to address them in future research and policy designs.

3.6.3 Sensitivity analysis and limitations

To further test the validity of the conclusions, sensitivity analysis is conducted to explore how the uncertainties about the underlying assumptions may influence the conclusions of the study. In this study, the uncertainties can come from various aspects of the model – the driving patterns of the EVs, the generation portfolio in 2030, and so on. But among them, one of the most important sources of the concerns comes from the natural electricity load fluctuations. In our study, we have collected and used the average load curve as a typical daily load. However, since there are natural fluctuations of the loads due to the weather or other factors, and these fluctuations of the loads lead to non-linear results of the dispatch models, sensitivity analysis is required to test how the conclusions may stand under different demand assumptions. In particular, two extra cases are considered – “Low_Demand” and “High_Demand” side scenarios compared to the “Average_Demand” base scenario used in the study (see Section 3.5.3 for the definition and descriptions of these side cases). The full regional results can be found in Appendix 3.A.

Overall, these side cases show that the fluctuations of the loads can significantly bring uncertainties on how the EV adoptions influence the electric power grid. The incremental O&M costs increase significantly in the High_Demand scenario, compared to the Average_Demand scenario. This phenomenon reflects the “hockey stick” shaped nature of the electricity supply curves (Figure 3.9), illustrating the marginal cost escalates dramatically with the increase in the demands. For example, in the SERC-S region, under the average load burden assumption, the O&M cost additions due to EV adoptions are moderate, below 2 cents/kWh. However, when the electricity demand other than EV is high, the incremental O&M cost increases dramatically along with EV adoptions. In the EV37.5 High_Demand scenario, the incremental average O&M cost is

25.4 cents/kWh, about 3.9 times higher than its daily O&M cost relative to that in the Average_Demand base scenario.

Table 3-6 Sensitivity analysis of SERC-S: additional O&M costs of EV charging loads

	EV12.5			**EV25**			**EV37.5**		
	Average Demand	*Low Demand*	*High Demand*	*Average Demand*	*Low Demand*	*High Demand*	*Average Demand*	*Low Demand*	*High Demand*
million $	148.44	127.39	577.37	305.51	275.09	1386.52	483.57	431.47	6537.89
cent/kWh	1.73	1.48	6.71	1.78	1.60	8.06	1.87	1.67	25.35

The sensitivity analysis illustrates the limitation of using average load to examine the electric power operational costs. The non-linearity relationship between the electric grid O&M cost with the demand challenges the validity of treating average demand as a representative proxy of the grid management practice. It calls for a more concise way to measure the fluctuations of the loads, such as a probability-based loads model. However, due to the data available to measure this uncertainty, the study has not incorporated more considerations.

Another challenge limiting sensitivity analysis is the deterministic approach adopted in the generation resources to forecast the supply curves. The study adopts the forecasts from GT-NEMS resource availability to project the supply curves. The scenario is aligned with AEO 2018 reference case developed by US EIA but fails to adopt side cases to allow more sensitivity analysis. The generation resources from GT-NEMS are equilibrium outcomes based on various inputs and assumptions embedded in the original scenario setting. This study adopts these underlying assumptions implicitly when leveraging the data deterministically, neglecting the uncertainties associated with the GT-NEMS model and scenario settings. Future studies could benefit from expanding the sensitivity analysis to form confidence intervals in the conclusions and provide more reliable quantifications.

Furthermore, the supply curves developed do not consider many real-world constraints for unit commitment and electricity dispatch, such as reserve constraints, ramping rates constraints, transmission constraints. Although I introduce the time-sliced generation resource availability to simulate a more realistic simulation, the supply curves are still based on the least O&M cost pathways at each time slice. In the future, more studies can increase the validity by introducing more dispatching constraints to the supply curve, achieving better simulations of real-world power system operation practices.

In addition, the study also needs further examination in the static view of the regional driving patterns and charging behavior of EVs. This study has adopted many assumptions from historical observations, such as the vehicle-mile-travel (VMT) by region, emission factors for generation resources, and gasoline emission factor. Many of the parameters are also obtained for more general syneresis but apply to the region studies homogenously. For example, the charging speed and loss data, EV vehicle efficiency are borrowed from IEA, which applies to the projections of world EV outlooks, not specifically tailored to reflect the situations in my research areas. Meanwhile, the transportation sector is going through a series of revolutionary changes, and these changes may result in systematic structural changes in how people drive and charge their EVs regionally and differently compared to historical observations. This situation challenges the validity of the conclusions and calls for more sensitivity analysis to examine the adopt different regional assumptions. For one thing, this study has shown that based on NTHS 2017 surveys on how people drive and have a series of assumptions on EV charging, mainly with Level 2 chargers. With more EV charging stations available and more advanced charging technology deployed, such as Level 3 DC charging networks, the expectations of the behavior will be different. The changes in these assumptions embedded should be addressed in future studies to facilitate more accurate estimates and more concrete conclusions.

Last, many crucial components of costs associated with EV adoptions are not included in the analysis. Instead, only the variable O&M costs are examined in the study to reflect the additional costs for generations. Future work can benefit from adding the components of the unique infrastructure costs for EVs, such as the chargers, controls, and distribution feeder, forming more complete frameworks to examine the costs of EV adoptions.

Appendix 3.A. Sensitivity analysis of the existing loads on the costs of the generation serving EV charging demands

Table 3.A-1 SERC-S: Cost additions compared to the Reference scenario

	EV12.5			**EV25**			**EV37.5**		
	Average Demand	*Low Demand*	*High Demand*	*Average Demand*	*Low Demand*	*High Demand*	*Average Demand*	*Low Demand*	*High Demand*
million $	148.4	127.4	577.4	305.5	275.1	1386.5	483.6	431.5	6537.9
cent/kWh	1.73	1.48	6.71	1.78	1.60	8.06	1.87	1.67	25.35

Table 3.A-2 SERC-S: Percentage increase in hourly O&M cost compared to the Reference scenario

	EV12.5			**EV25**			**EV37.5**		
Time	*Average Demand*	*Low Demand*	*High Demand*	*Average Demand*	*Low Demand*	*High Demand*	*Average Demand*	*Low Demand*	*High Demand*
1	2.9%	2.6%	3.6%	5.8%	5.1%	7.3%	8.7%	7.9%	11.2%
2	1.5%	1.3%	1.8%	3.0%	2.6%	3.7%	4.5%	4.0%	6.3%
3	0.7%	0.6%	0.8%	1.4%	1.2%	1.7%	2.0%	1.8%	2.5%
4	0.3%	0.2%	0.3%	0.5%	0.5%	0.7%	0.8%	0.7%	1.0%
5	0.1%	0.1%	0.1%	0.2%	0.2%	0.2%	0.3%	0.3%	0.4%
6	0.1%	0.0%	1.0%	0.1%	0.1%	2.1%	0.2%	0.1%	3.1%
7	0.1%	0.1%	1.9%	0.2%	0.2%	3.9%	0.3%	0.3%	5.8%
8	0.2%	0.2%	4.9%	0.5%	0.4%	9.7%	0.8%	0.6%	14.6%
9	0.6%	0.5%	11.3%	1.2%	1.0%	22.6%	1.8%	1.5%	34.0%
10	1.3%	1.1%	24.9%	2.6%	2.2%	49.8%	4.1%	3.3%	74.7%
11	2.6%	2.1%	2.9%	5.1%	4.4%	5.8%	7.7%	6.6%	8.8%
12	4.4%	3.8%	4.7%	9.0%	7.7%	9.4%	13.4%	11.5%	14.1%
13	7.2%	6.1%	7.5%	14.4%	12.3%	16.7%	21.0%	18.8%	23.2%
14	11.7%	10.1%	14.7%	26.3%	21.2%	29.9%	39.8%	32.1%	41.4%
15	14.8%	12.6%	15.6%	30.9%	25.9%	33.4%	43.6%	43.9%	871.7%
16	18.7%	15.9%	20.0%	40.0%	32.7%	48.1%	62.9%	55.4%	1096.9%
17	21.5%	18.3%	22.9%	41.9%	42.3%	61.3%	72.1%	64.0%	1257.5%
18	21.7%	19.2%	25.9%	43.8%	44.2%	50.3%	76.0%	66.8%	1313.7%
19	21.3%	18.2%	22.2%	41.7%	42.0%	46.8%	71.7%	63.6%	1250.5%
20	19.4%	16.6%	22.1%	40.6%	34.1%	45.1%	57.4%	57.8%	65.8%
21	15.6%	13.8%	312.1%	36.1%	31.5%	624.1%	58.9%	49.7%	936.2%
22	12.4%	10.1%	232.8%	23.3%	20.7%	465.7%	35.0%	31.2%	698.5%
23	8.7%	7.0%	11.3%	17.4%	14.9%	343.0%	27.3%	22.5%	514.5%
24	5.0%	4.5%	6.3%	11.3%	9.1%	12.9%	16.9%	13.8%	24.9%
Daily	**8.8%**	**7.5%**	**34.2%**	**18.1%**	**16.3%**	**82.1%**	**28.6%**	**25.5%**	**387.0%**

Table 3.A-3. NYISO: Cost additions compared to the Reference scenario

	EV12.5			EV25			EV37.5		
	Average Demand	*Low Demand*	*High Demand*	*Average Demand*	*Low Demand*	*High Demand*	*Average Demand*	*Low Demand*	*High Demand*
million $	405.1	54.06	586.6	812.6	111.8	1177.3	1433.2	199.6	1852.6
cent/kWh	13.65	1.82	19.77	13.69	1.88	19.83	16.10	2.24	20.81

Table 3.A-4. NYISO: Percentage increase in hourly O&M cost compared to the Reference scenario

	EV12.5			EV25			EV37.5		
Time	*Average Demand*	*Low Demand*	*High Demand*	*Average Demand*	*Low Demand*	*High Demand*	*Average Demand*	*Low Demand*	*High Demand*
1	5.5%	4.4%	91.5%	11.4%	8.7%	183.1%	18.0%	13.1%	274.6%
2	3.5%	3.3%	69.2%	7.1%	6.6%	138.3%	12.5%	9.9%	207.5%
3	2.0%	1.9%	4.5%	4.1%	3.8%	9.1%	6.2%	5.8%	122.9%
4	0.8%	0.8%	1.7%	1.7%	1.6%	3.5%	2.5%	2.4%	5.2%
5	0.7%	0.7%	1.1%	1.4%	1.3%	2.3%	2.1%	2.0%	4.3%
6	0.5%	0.4%	1.0%	0.9%	0.9%	2.0%	1.4%	1.3%	3.0%
7	0.2%	0.2%	4.4%	0.4%	0.4%	8.8%	0.7%	0.6%	13.1%
8	0.2%	0.1%	3.0%	0.4%	0.3%	6.1%	0.6%	0.4%	9.1%
9	0.3%	0.1%	3.0%	0.6%	0.3%	6.1%	0.9%	0.4%	9.1%
10	1.0%	0.0%	1.0%	2.1%	0.1%	2.1%	3.1%	0.1%	3.1%
11	0.2%	0.1%	0.2%	0.3%	0.3%	0.4%	0.5%	0.4%	0.6%
12	2.2%	2.1%	2.7%	4.4%	4.2%	5.7%	6.6%	6.4%	8.5%
13	2.3%	2.2%	3.0%	4.6%	4.4%	6.2%	6.9%	6.6%	9.7%
14	2.6%	2.5%	3.7%	5.5%	5.1%	7.6%	8.2%	7.6%	11.5%
15	1.1%	1.0%	1.4%	2.2%	2.0%	3.0%	3.3%	3.0%	4.6%
16	1.0%	0.9%	1.3%	2.0%	1.8%	2.8%	3.0%	2.8%	4.2%
17	1.7%	1.5%	2.1%	3.4%	3.0%	4.3%	5.1%	4.9%	6.4%
18	3.6%	3.4%	5.1%	7.3%	6.8%	10.6%	10.9%	10.1%	16.5%
19	8.5%	7.9%	12.0%	17.1%	16.2%	26.0%	26.6%	24.3%	56.5%
20	11.7%	10.9%	15.9%	23.6%	22.3%	34.6%	36.8%	33.6%	72.6%
21	142.9%	8.6%	142.9%	285.9%	18.8%	285.9%	428.8%	43.2%	428.8%
22	144.7%	8.7%	144.7%	289.4%	19.0%	289.4%	434.1%	43.7%	434.1%
23	101.4%	5.1%	101.4%	202.9%	10.2%	202.9%	304.3%	18.4%	304.3%
24	10.5%	5.0%	104.1%	23.1%	10.0%	208.3%	312.4%	15.6%	312.4%
Daily	**24.2%**	**3.2%**	**35.0%**	**48.5%**	**6.7%**	**70.3%**	**85.5%**	**11.9%**	**110.6%**

Table 3.A-5. Cal-ISO: Cost additions compared to the Reference scenario

	EV12.5			EV25			EV37.5		
	Average Demand	*Low Demand*	*High Demand*	*Average Demand*	*Low Demand*	*High Demand*	*Average Demand*	*Low Demand*	*High Demand*
million $	550.2	229.60	634.79	1129.2	546.9	1269.6	1697.6	976.1	1904.4
cent/kWh	8.11	3.38	9.36	8.32	4.03	9.36	8.34	4.80	9.36

Table 3.A-6. Cal-ISO: Percentage increase in hourly O&M cost compared to the Reference scenario

	EV12.5			EV25			EV37.5		
Time	*Average Demand*	*Low Demand*	*High Demand*	*Average Demand*	*Low Demand*	*High Demand*	*Average Demand*	*Low Demand*	*High Demand*
1	26.4%	0.0%	33.6%	52.9%	44.5%	104.3%	80.5%	75.0%	395.1%
2	24.9%	0.0%	26.3%	49.9%	0.0%	52.7%	75.1%	0.0%	79.1%
3	24.7%	0.0%	26.1%	49.6%	0.0%	52.2%	74.5%	0.0%	79.3%
4	46.5%	0.0%	49.1%	93.4%	0.0%	98.3%	140.0%	0.1%	147.4%
5	27.6%	0.0%	29.2%	55.2%	0.0%	58.3%	83.1%	0.0%	87.5%
6	9.4%	0.0%	10.0%	18.9%	0.0%	20.2%	28.4%	0.0%	30.2%
7	4.9%	0.0%	5.1%	9.7%	0.0%	10.3%	14.6%	0.0%	15.4%
8	2.9%	0.0%	3.8%	5.8%	0.0%	7.7%	9.0%	0.0%	12.4%
9	2.9%	0.0%	14.4%	5.8%	0.0%	28.7%	8.6%	0.0%	43.1%
10	1.5%	0.0%	7.6%	3.1%	0.0%	15.2%	4.6%	0.0%	22.8%
11	1.4%	0.0%	2.1%	2.9%	0.0%	4.5%	4.3%	0.0%	6.9%
12	1.7%	0.0%	8.4%	3.4%	0.0%	16.8%	5.1%	0.0%	25.2%
13	2.6%	0.0%	12.7%	5.2%	0.0%	25.4%	7.8%	0.0%	38.2%
14	3.3%	0.0%	16.0%	6.5%	0.0%	32.1%	9.9%	0.0%	48.1%
15	4.0%	0.0%	19.4%	9.0%	0.0%	38.8%	14.8%	0.0%	58.3%
16	6.7%	0.0%	24.2%	15.6%	0.0%	48.4%	72.7%	2.3%	72.7%
17	25.3%	0.0%	25.3%	50.5%	8.5%	50.5%	75.8%	14.2%	75.8%
18	80.1%	0.0%	85.8%	160.9%	0.0%	171.8%	243.8%	0.0%	258.6%
19	64.1%	12.2%	64.1%	128.1%	24.8%	128.1%	192.2%	38.5%	192.2%
20	79.0%	15.2%	79.0%	157.9%	31.7%	157.9%	236.9%	48.2%	236.9%
21	99.8%	20.0%	99.8%	199.5%	40.7%	199.5%	299.3%	87.7%	299.3%
22	96.4%	19.3%	96.4%	192.8%	39.4%	192.8%	289.2%	73.9%	289.2%
23	88.6%	17.1%	88.6%	177.2%	35.5%	177.2%	265.9%	54.2%	265.9%
24	22.3%	20.4%	109.4%	50.9%	41.8%	218.8%	113.3%	63.4%	328.2%
Daily	**36.8%**	**6.6%**	**44.9%**	**74.1%**	**15.3%**	**90.6%**	**116.6%**	**26.3%**	**141.0%**

CHAPTER 4. MACRO-ECONOMIC DEVELOPMENT CASE STUDY: THE LONG-TERM IMPACTS OF ELECTRIC VEHICLES ON GRID OPERATIONS AND CONSUMER BILLS FOR THE SOUTHEAST, NEW YORK, AND CALIFORNIA

In the third study of this thesis, I explore the co-benefits and co-costs from the EV mandate policy on the long-term impacts of electric vehicle policies on grid operation cost, electricity rates, and consumer bills. This analysis expands the work done in Chapter 3 by extending the time scope to allow the grid to evolve in capacity planning and rate setting. It also employs broader coverage to examine the macro-economic impacts on the electric power sector, transportation sector, and other end-use sectors. Specifically, leveraging on the GT-NEMS, this study simulates a series of national Zero-Emission Vehicle Standard (ZEV) policies to cover 25, 50, and 75 percent of the new vehicle sales for the whole U.S. from 2030 to 2050. At both national and regional levels, the results demonstrate the impacts of EV mandates on societal cost savings and carbon emission reductions. Besides the ZEV mandates, Vehicle-to-Grid (V2G) is also added as alternative scenarios to explore the customer-utility partnership potentials. Lastly, similar to Chapter 3, three case studies of the Southeast (SERC-S), New York ISO(NYISO), and California ISO(Cal-ISO) are conducted. The regional analysis explains regional heterogeneities, highlighting the possibility of inter-regional wealth transfers and raising equity concerns.

4.1 Introduction

This study is an extension of Chapter 3, expanding the time scopes and the sectoral coverage to show the direct (as in Chapter 3) and the indirect and induced macro-economic impacts. Various studies have revealed the differences between short-term "passive" and long-term "active" roles that the utilities can participate in EV charging (Arias & Bae, 2017; Azadfar, Sreeram, & Harries, 2015; Pradel, Fulda, & Huber, 2016; Sun, Yamamoto, & Morikawa, 2015; Tan et al., 2016). In the short term, the electric grid will only treat EV as a source of electricity demand without further unit planning and coordination. While on the long run, several studies have shown the more potential cost-savings both for the EV owners and the utilities with appropriate planning, advanced technology, and innovative business models (Arias & Bae, 2017; Azadfar et al., 2015; H. Wang & Wang, 2014; K. Zhou, Fu, & Yang, 2016; K. Zhou et al., 2016).

Among these consumer-utility partnership opportunities, the Vehicle to Grid (V2G) technology, a smart grid technology allowing certain interaction levels between electric vehicles and power grid, has attracted significant attention. It has proven to provide theoretical and empirical benefits to vehicle owners and the power grid (Arias & Bae, 2017; Azadfar et al., 2015; H. Wang & Wang, 2016). Besides, V2G utilizes the communication between the power grid operator and EV to throttle the charging rate of each EV, preventing grid overloading, system instability, and voltage drop issues. If energy exchange between the EV battery and the power grid is enabled, V2G can provide greater flexibility for the power utility to control the EV battery energy to improve the reliability and sustainability of the power system (Brown & Soni, 2019; Wolbertus et al., 2018; Sovacool et al., 2017; Xie et al., 2019; Almutairi et al., 2018; Tan et al., 2016; Fitzgerald et al., 2016; Sovacool & Hirsh, 2009).

Nevertheless, the importance of understanding the impacts of EVs and related policies is urgent. However, for long-term macro-economic impacts, the quantification efforts are even more scarce – reliable and systematic estimations on the existence and the magnitude of the effects of EV policies are challenging due to the complexities of understanding policy response behaviors characterizing the cross-sectoral indirect and induced impacts. As a result, the previous studies either approached the issue most qualitatively (Brown & Soni, 2019; Wolbertus et al., 2018; Sovacool et al., 2017; Xie et al., 2019; Almutairi et al., 2018; Tan et al., 2016; Fitzgerald et al., 2016; Sovacool & Hirsh, 2009) or used simplified technological-based simulations (Hashemi et al., 2018; Zhang et al., 2018; Alizadeh et al., 2016; Rahbari-Asr et al., 2016; Umeano, 2016; Su et al., 2014; Marols et al., 2014; Buekers, Van Holderbeke, Bierkens, & Int Panis, 2014; Han et al., 2015; Anastasiadis et al., 2017).

Besides, similar to the short-term, the long-term regional heterogeneity of the EVs and the grid integrations require further research (Choi et al., 2013; Al-Alawi & Bradley, 2013b; Buekers et al., 2014). The majority of the regional case studies have focused on California (Coignard et al., 2018; Jiang, 2017; Noori et al., 2016; Xu et al., 2018), which cannot be considered a good representative of all other regions. Many of the previous regional studies have focused on one region, such as New York State (Mohamed, 2019), California (Jiang 2017; Ma et al., 2012), Virginia-Carolina (Hadley, 2006), and Pacific Northwest (Schneider et al., 2006). In comparison, Choi et al. compares six regions in the Eastern Interconnection (Choi et al., 2013) and prove the regional differences in electric power sectoral response to the EV penetration. However, the analysis focuses on the direct impacts of EV penetration on grid management, failing to consider the macro-economic effects of induced changes. It examines the cost of generation due to EV penetration without the process of electricity rate-setting and consumer response to changed electricity prices.

Meanwhile, with more and more states join the California ZEV, there have been significant discussions about taking the mandate nationally. The current California law was established in 2018 and has planned to increase the requirement until 2025 gradually. Starting from 2026 and the subsequent model years, a manufacturer must meet a total ZEV credit percentage of 22%. Also, the maximum portion of a manufacturer's credit percentage requirement that may be satisfied by Transitional Zero-Emission Vehicles (TZEV) credits is limited to 6% of the manufacturer's applicable California PC and LDT production volume. TZEVs covers certified Bi-fuel, fuel-flexible, and dual-fuel/hybrid vehicles and introduces partial credit calculation systems to be exchangeable for ZEV credits.

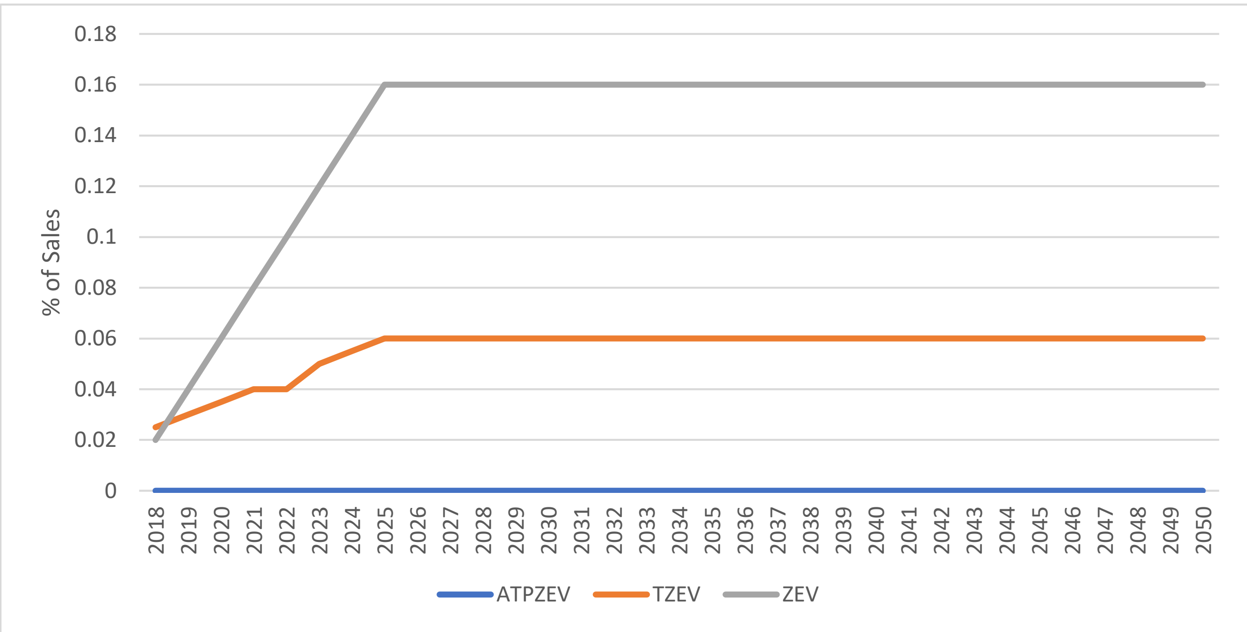


Figure 4-1 Requirements of the California ZEV standards

Source: California Code of Regulations 13 CA ADC § 1962.2,

Along with California, 14 states have previously committed to one or several emission regulations on the transportation sector similar to California. The coverage of LEV regulations (not including Virginia) has already covered about 35.8% of all U.S. new LDV sales and ZEV for 29.9% of it (Figure 4-2). In 2021, Virginia is considering becoming the 16th state electing the state rules, which adds to the debates over a state-wide plan for EV mandates.

Table 4-1 States committed to join ZEV programs before 2021

State	Applicable MY			State's share (%) of U.S. New Light-Duty Vehicle Sales*
	LEV Regulations		ZEV Program	
	Criteria Pollutant Regulation	GHG Regulation		
California	1992	2009	1990	11.7%
New York	1993	2009	1993	6.0%
Massachusetts	1995	2009	1995	2.1%
Vermont	2000	2009	2000	0.3%
Maine	2001	2009	2001	0.4%
Pennsylvania	2001	2009		3.9%
Connecticut	2008	2009	2008	1.0%
Rhode Island	2008	2009	2008	0.3%
Washington	2009	2009		1.8%
Oregon	2009	2009	2009	1.0%
New Jersey	2009	2009	2009	3.5%
Maryland	2011	2011	2011	2.0%
Delaware	2014	2014		0.3%
Colorado	2022	2022	2023	1.6%

Source: California Air Resources Board, 2021.

4.2 Motivation/Research questions

In this research, I focus on solving the puzzle by quantifying the national ZEV mandate policies' societal impacts. Filling the current research gap, this study sheds light on the more systematic and comprehensive evaluations of the potential long-term implications of EV mandate policies on macroeconomics. These ZEV mandates are also coupled with V2G options to illustrate the impacts of synergic effects. Besides, the regional disparities are examined by conducting the case studies of the Southeast, New York ISO, and California ISO territory.

Overall, the detailed research questions are framed in four questions:

(1) *What are the influences of massive adoptions of electric vehicles on grid operational costs and* CO_2 *emissions in the long term?*

(2) *What are the influences on rates and consumer bills for residential, commercial, industrial, and transportation sectors, respectively?*

(3) *What are these influences on grid management and consumer bills changed by coordinated charging and other ancillary services?*

(4) *What are these regional differences in the influences on grid management and consumer bills changed by EV adoptions?*

4.3 Hypotheses

The hypotheses are closely connected to the questions raised. To answer each of the questions, four hypotheses are proposed.

Hypothesis 4.1: In the long run, capacity planning could enable policy-driven electric vehicle penetration to lower CO_2 ***emissions and total costs.***

Hypothesis 4.2: The policy-driven electric vehicle penetration could decrease the electricity rates for all sectors as the utilities lower their grid operational costs, thus reducing the electricity bills for the residential, industrial, and commercial sectors.

Hypothesis 4.3: The policy-driven electric vehicle penetration could decrease operation costs and consumer bills, which are further reduced by introducing EV-grid partnerships to allow coordinated charging and ancillary services from grid-EV integrations.

Hypothesis 4.4: The regions with higher intermittent renewable resources and higher electricity prices could benefit from the policy-driven electric vehicle penetration. Thus, California could receive the most significant overall benefits in grid cost savings, CO_2 ***emission reductions, and consumer bill savings. However, with the anticipated rapid solar adoptions, the Southeast will have higher growth rates in these benefits.***

Correspondingly, to test these hypotheses, I first examine the Total Resource Costs (TRC) and the electric power sector's carbon dioxide emissions. Besides, electricity rates and sectoral electricity spending are analyzed to show the electricity bill changes across scenarios. Last, the transportation and other end-use sectors' energy usage and corresponding carbon dioxide emissions are also examined.

4.4 Methodology

The methodology is detailed explained in this section. Since the research regions are the continental U.S. and the case study regions similar to Chapter 3 (see Chapter 3, 3.4.1 for details), this study skips the brief introductions of the research area. Thus, this section focuses on the model structure and the scenario settings used in the analysis.

The integrated assessment of the ZEV mandates on the macro-economics is conducted using GT-NEMS because of its data's currency and the transparency and open-source nature of the model fully described in an array of published documentation. Another merit of the model is the ability to conduct multi-sectoral macro-economic impacts over specific policy shifts. The general structure and in particular, the electricity modules are described in Chapter 2 and Chapter 3 (see Chapter 2, Appendix A and Chapter 3, 3.4.2 for details).

Similarly, the business-as-usual scenario is the same as the Reference case used in Chapter 2 and Chapter 3, consistent with AEO 2018 developed by US EIA. Based on the Reference case, side cases are set to reflect an array of options in the EV mandates starting in 2030 – 25, 50, and 75 percent of ZEV requirements for new vehicle sales. This requires changing the parameters in one of the input file collections, "TRNLDVX.xlsx". Besides, to model V2G options, "ECPDATYN.txt" is updated. Due to the GT-NEMS developing structure, the researchers cannot directly shift the electric vehicles' EV charging demands conditionally on the battery status or traveling patterns. Thus, the model treats V2G technology as an optional resource providing low-cost demand-response capacity for the grid, 25% lower than the original demand-side management costs in the Reference case. Also, the V2G option is modeled to increase demand-side resources' availability to shift demands from peak to off-peak hours, which is equivalent to charging-grid demand coordination. The peak-shifting abilities depend on the electric vehicle battery capacities and are assumed to increase gradually over the year from 60% in 2030 to reach full capacity in 2050.

4.5 Results

4.5.1 EV mandate impact on EV adoptions

In the absence of the national ZEV mandates, GT-NEMS forecasts that the annual national EV sales will grow steadily, around 7.5% year-to-year from 2030 to 2050 (Figure 4-2). These sales will increase the EV in total vehicle stock from about 5% in 2030 to 15% in 2050. In contrast, in all of the ZEV mandate scenarios, the GT-NEMS model estimates additional EV uptakes. Each ZEV requirement increment would precipitate additional EV sales, ranging from 0.7 M, 32% increase relative to the Reference scenario to 2.5M each year 119% increase relative to the

Reference scenario, thus increasing the EV total stock accordingly. Naturally, the EV stock changes will lag the sales showing total EV stocks will take up to 38.4% in the EV75 scenario relative to 15.7% in the Reference scenario.

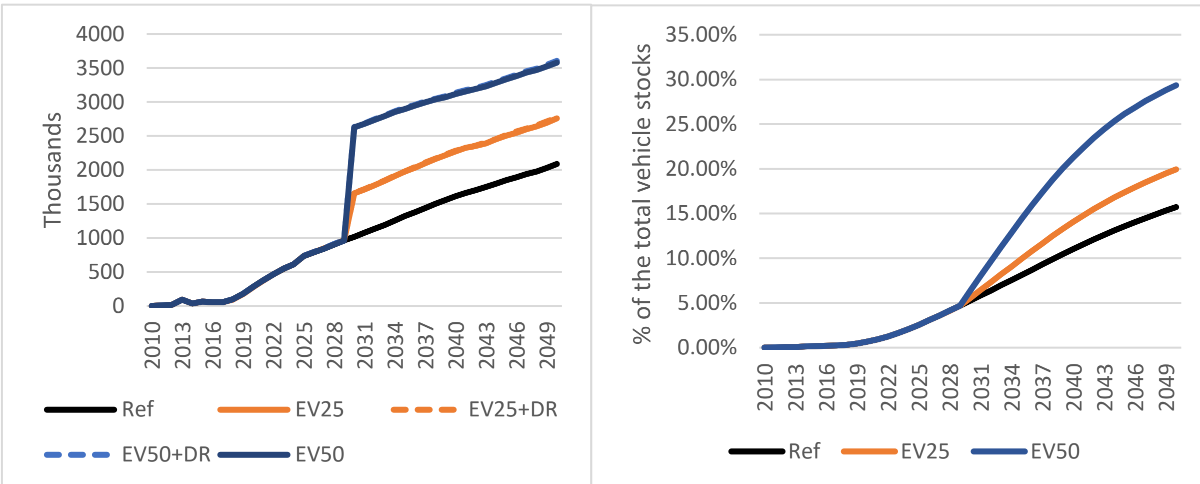


Figure 4-2 ZEV mandates on EV yearly sales (left) and EV stocks (right)

As the total vehicle fleet becomes more electrified, the petroleum usages in the transportation sector will decrease, reducing the consumer's bills (Figure 4-3). The reductions are substantial – the EV adoptions fall petroleum bills up to $146.9B (38.7%) in the EV75 scenario. Adding V2G will not alter the consumer behavior directly; thus, the additional change when adding V2G is minimal.

Figure 4-3 ZEV mandates on petroleum bills

4.5.2 EV mandate impact on electricity generation fuel mix

GT-NEMS aligns with the AEO 2018 projections in the Reference scenario that in 2050, the generation fuel mix is 21.4% from coal, 11,8% from nuclear, 35.3% from natural gas, 5.5% from hydro, 14.4% from solar, and 8.3% from wind respectively (Figure 4-4). Applying electric vehicles by ZEV mandates will change limited aspects of the generation fuel mix relative to the Reference scenario. First, the policy-induced EVs increase the total loads slightly. The effects are minor, ranging from a 2% increase in EV25 to a 7% increase in EV75, reflecting the total EV fleets' size relative to the electricity demands. Coupling V2G adoptions to EV increases the total demand, resulting from the fact that the electricity prices are lower, thus attracting higher consumptions. However, this rebound effect is less than a 1% increase relative to the total demand.

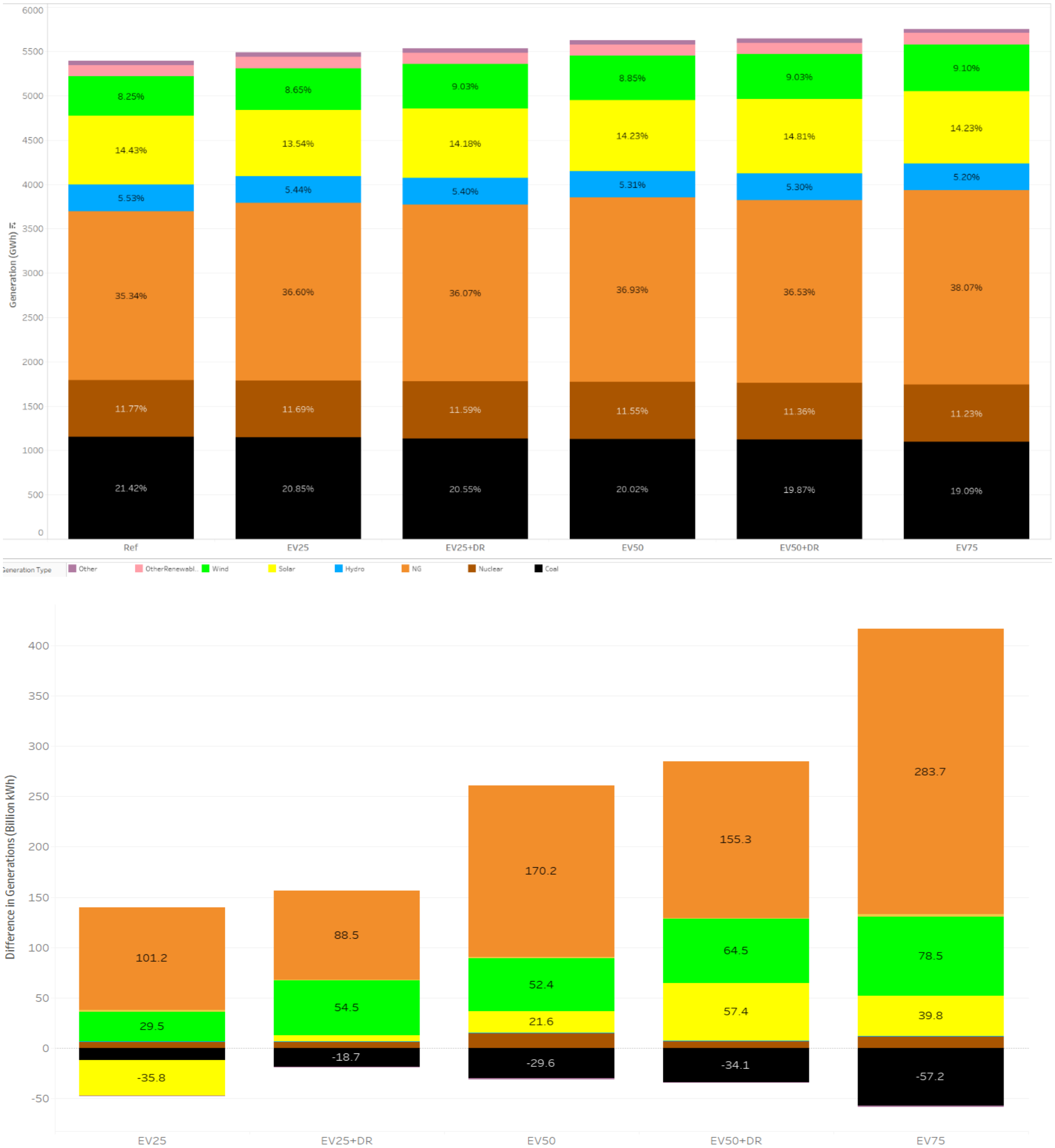


Figure 4-4 Generation by type in 2050 in total (above) and differences relative to the Reference (below)

Second, besides the total demand change, the generation fuel mix also shifts (Figure 4-4 below). Compared to the Reference scenario, ZEV mandates boost natural gas generation dramatically by 101.2 GWh to 283.7 GWh (0.3 to 0.8% of total generation). These natural gas uptakes replace coal generation up to 57.2 GWh/year, around 5% of the entire coal generation in the Reference scenario. Adding V2G to the ZEV mandates further accelerates the electricity generation from solar and wind. For example, in 2050, the EV50+V2G scenario utilizes 35.8GWh more solar electricity generation and 12.1GWh more wind generation relative to the EV50 scenario.

4.5.3 EV mandate impact on electricity bills and total resource costs

The shift in the generation fuel mix alters the electricity price. More EV adoptions increase electricity prices 1.5% to 5.3% relative to the Reference scenario respectively for the EV25 and EV75 scenario (Figure 4-5 above). Over time, the electricity prices escalate with more adoptions of EVs. However, when coupled with the V2G option, the electricity prices are projected to increase slower, even decrease over time. In 2050, adding V2G will lower the price by about 1.8 percent relative to the scenario without V2G. What's more, the EV25+V2G scenario demonstrates the electricity prices even lower than that of the Reference scenario by about 0.16 cent per kWh.

The aggregate effects of the shifts in the electricity price and total electricity consumptions are shown in the electricity bills (Figure 4-5 below). Overall, all ZEV mandates increase the total electricity bills since they increase the electricity demands. In 2050, the Reference scenario's electricity bills are around 502.2 billion $ while in the EV75 scenario, consumers pay about 60 billion $ extra, 11.9% higher. In contrast, adding V2G to the ZEV mandates can ease the burden of the electricity demands by about 2% to 3%.

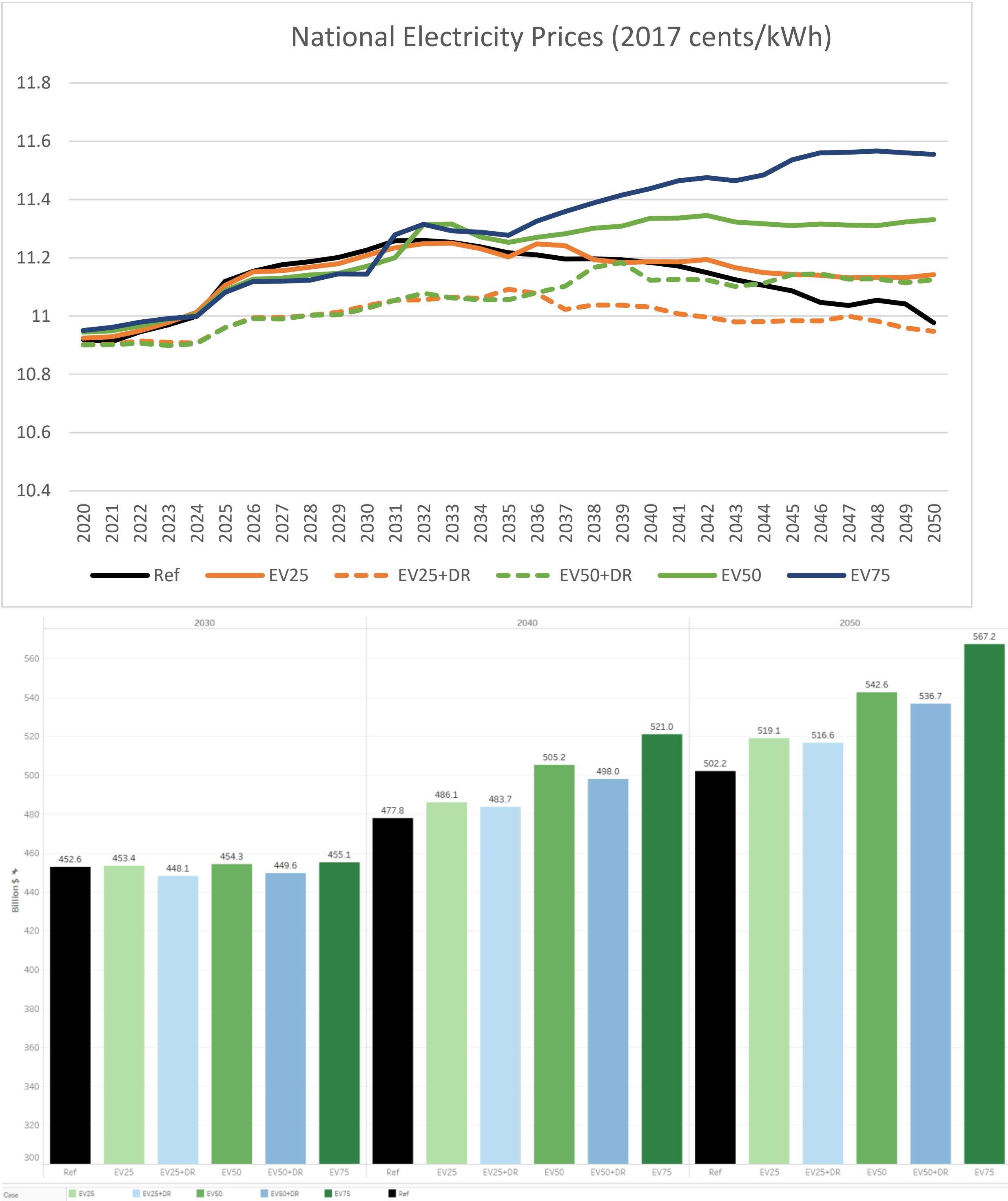
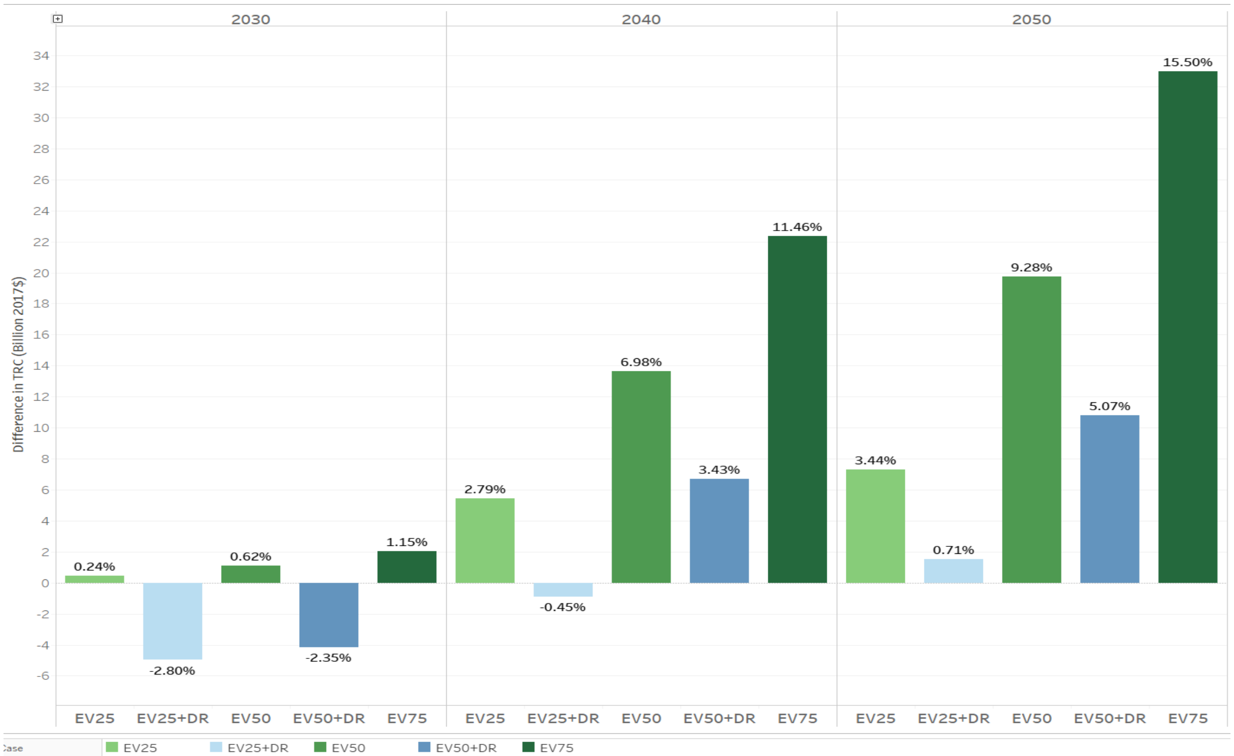


Figure 4-5 Electricity prices (above), and electricity bills in 2030, 2040, and 2050(below)

Total Resource Cost (TRC) is examined in this study to measure the total cost of utility management, including energy and capacity-related costs, additional resources savings, incremental capacity expansion costs, and generation overhead costs. Compared to some other common measurements of costs, such as levelized cost of electricity (LCOE) used in other studies (Choi et al., 2013; Tan et al., 2016b), TRC has the merits to introduce the program administration costs and advanced financial options that the utilities adopt. Figure 4-6 describes the outcomes of incremental TRC compared to the Reference case. We see the EV adoptions without V2G increase total TRC. A higher level of ZEV mandates will increase the TRC substantially compared to the Reference case. The incremental TRC also increases over time as the EV demand gets larger, requiring more costs on fuel and capacity expansions. Adding V2G will lower the TRC substantially. Compared to the EV50 scenario, in 2050, EV50 plus V2G scenario will 9.9 billion dollars per year, about a 3.7% reduction.

However, the overall TRC increase does not necessarily mean a higher average cost of generation. On the contrary, examining the TRC per generation (Figure 4-6 below), we forecast the EV penetration lower the average costs per generation in 2030 than the Reference scenario. TRC per generation increases over time primarily due to the expansions of natural gas and renewable generation capacities shown in Section 4.5.2. In addition, adding V2G decreases the costs per generation. In addition, the benefits of V2G increase over time. Compared to the EV50 scenario, adding V2G lowers the TRC per generation by 3.20%, 3.76%, and 4.58% in 2030, 2040, and 2050.



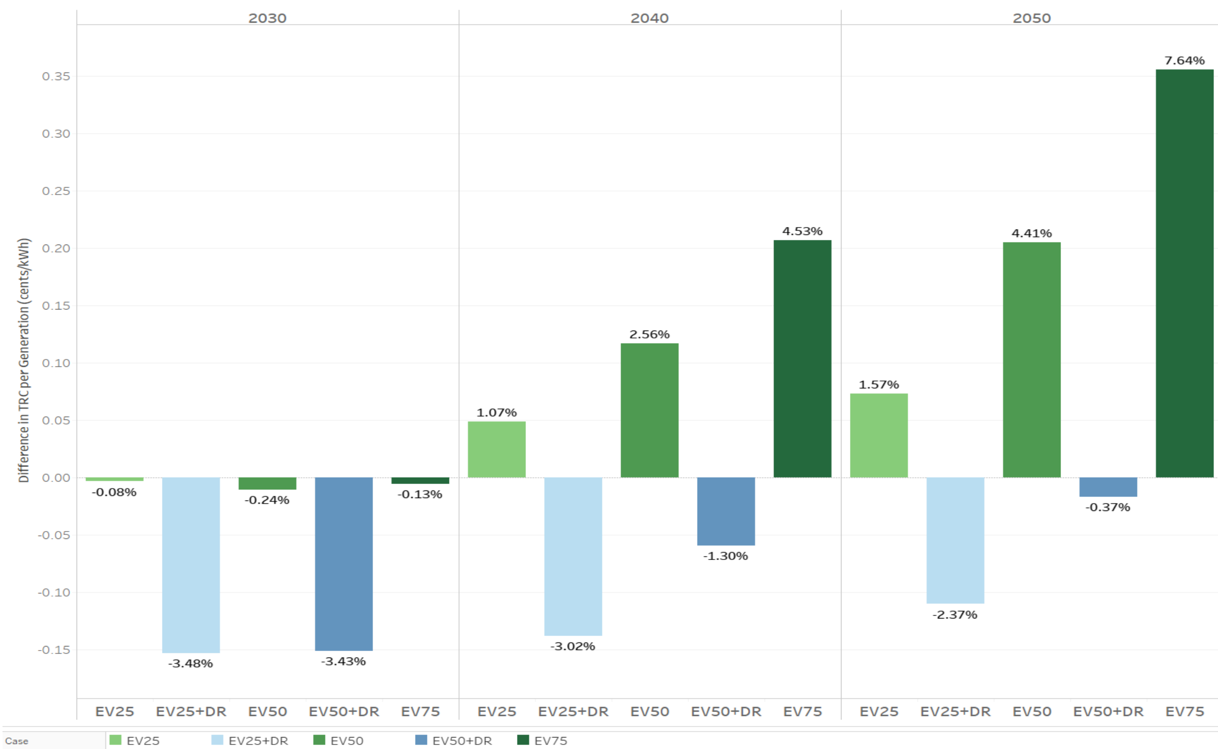


Figure 4-6 Total Total Resource Costs (TRC) increments (above) and TRC/Generation increments (below) compared to the Reference in 2030, 2040, and 2050

4.5.4 EV mandate impact on carbon dioxide emissions

The carbon dioxide change reflects the change in total electricity generation and its generation fuel mix, transportation gasoline avoided, and the macro-economic impacts from other end-use sectors. Correspondingly, the total societal carbon dioxide emission reductions are the sum of three components: electric power sectoral reductions avoided petroleum from the transportation sector and other end-use sectors (Table 4-2). As the electricity demands grow, the total carbon dioxide emissions are higher. For example, the EV50 scenario increases the carbon dioxide emission from the electric power sector by 27.5 million metric tons in 2050, about 1.4% of the electric power sector's carbon dioxide emissions. However, the extra emissions are compensated by considerable benefits from avoiding petroleum and slightly end-use sectoral emission reductions induced by lower electricity price induced fuel switching. Thus the overall total emission reductions are positive savings of 164.6 million metric tons in 2050, which is around 3.1% of the total emissions in the Reference scenario. Besides, adding the V2G option as a demand response resource increases overall emission reductions by 4.3 million metric tons, primarily due to the generation fuel mix to adopt more renewables.

Table 4-2 The carbon dioxide emission reductions in 2050 (million metric tons)

Ref	EV50				EV50+DR			
Total Emission	**Total Emission Reduction**	Electric Power Reduction	Petroleum Reduction	Other	**Total Emission Reduction**	Electric Power Reduction	Petroleum Reduction	Other
5278.8	164.6	-27.5	183.2	9.0	168.9	-23.8	182.1	10.6

4.5.5 Regional case study – SERC-S

Facing similar policy requirements, the regions may not necessarily follow the U.S.'s similar trends, illustrating regional heterogeneities. Several factors contribute to the regional heterogeneities, including regional resource availability and price elasticity, and so on. In this study, we explore the regional differences by examining three regions.

Unlike the national average, SERC-S relies more on fossil fuel to generate electricity (**Figure** 4-7). In the Reference scenario, coal generation is steadily decreasing but remains about 20.4% of the entire generation. Natural gas and nuclear are expanding the generation but slower than the pace of the total electricity demand. In other words, the massive adoptions of solar push the relative portion of natural gas and nuclear lower from 42.1% and 23.9% respectively in 2030 to 42.1% and 23.9% respectively in 2050.

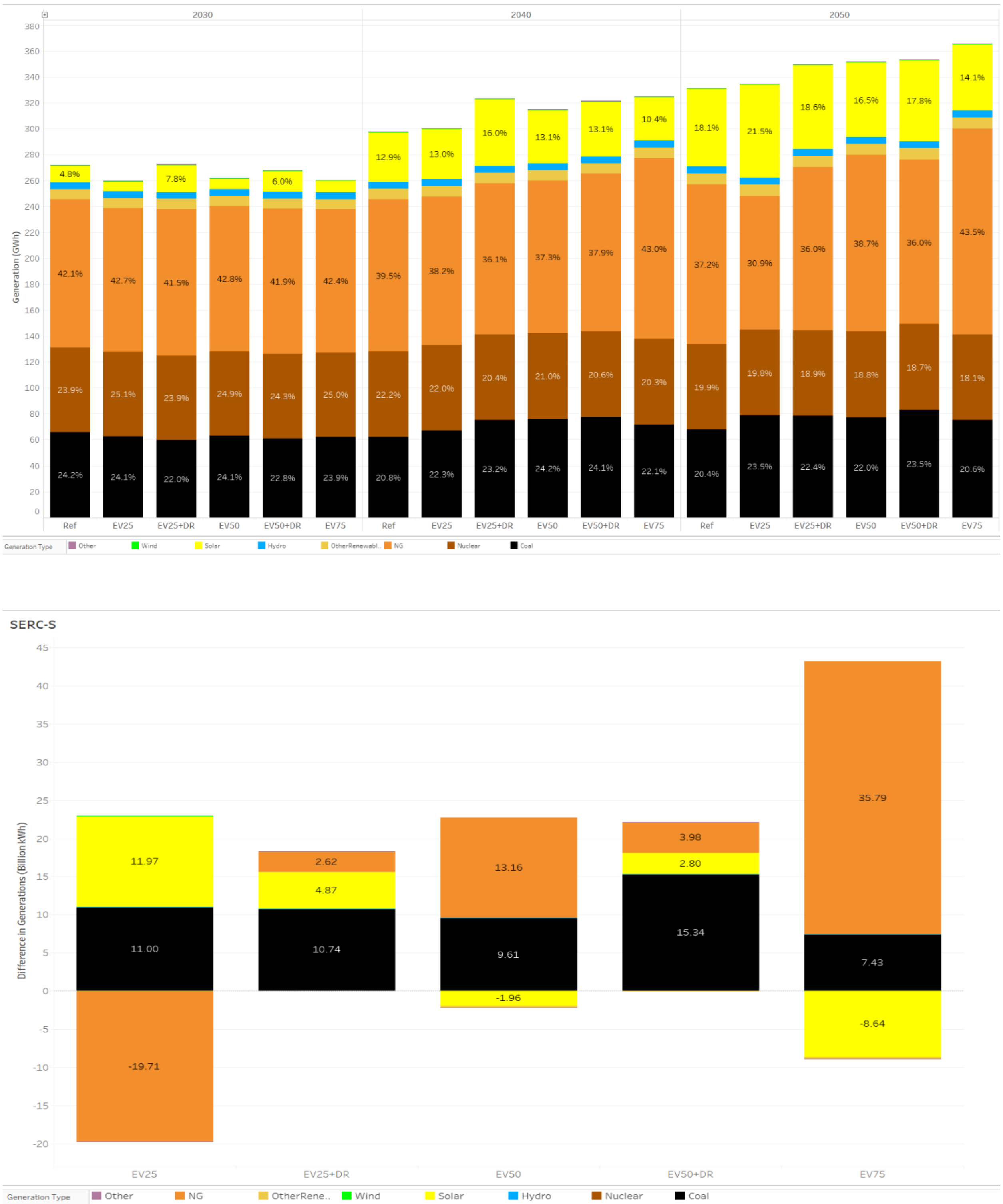


Figure 4-7 SERC-S: generation by type in 2030, 2040, 2050 in total (above) and differences relative to the Reference (below)

Overall, for SERC-S, the combinations of natural gas, coal, and solar are the generation resources satisfying extra charging demands. Unlike the national trends, the coal uptakes in all scenarios are substantial. For example, in the EV50 scenario, coal generation increases about 14.3% relative to the Reference scenario, taking about 46.6% of the additional electricity generation. However, the charging demands are met differently across scenarios. ZEV mandates work differently in terms of the total electricity generation and the generation fuel mix (Figure 4-6). In 2050, 19.71 billion kWh is forecasted to reduce natural gas generation for the EV25 scenario. In contrast, coal generation increases by 11.0 billion kWh, and solar generation grows 11.97 billion kWh, about 18.3%. However, in the EV50 scenario, the solar generation is reduced slightly by about 3.2%, while the majority of the extra electricity demands are satisfied with coal and natural gas. Adding V2G options further shows different impacts for different levels of the ZEV mandates – either reduce coal in the EV25+V2G scenario or increase coal when V2G is added to the EV50 scenario.

The inconsistency across the scenarios has reflected the regional heterogeneities in resource availability and price-elasticities in various decision-making. It is hard to decipher one factor contributing to the shifts rather than a systematic movement of every aspect of macroeconomics.

As a result of the generation fuel mix, the carbon dioxide emissions differ among different scenarios (Table 4-3). Compared to the overall emissions of 233.1 million metric tons in the Reference scenario in 2050, total emission reductions are about 2.9% and 1.7% for the EV50 and EV75 scenarios. The results reflect the energy usage shift from transportation petroleum and the other end-use sectors' electrification to the electric power sector. As shown in Figure 4-6, the V2G option increases coal uptakes, thus increasing the electricity carbon emissions and reducing the overall carbon emission benefits.

Table 4-3 SERC-S: the carbon dioxide emission reductions in 2050 (million metric tons)

Ref	EV50				EV50+DR			
Total Emission	**Total Emission Reduction**	Electric Power Reduction	Petroleum Reduction	Other	**Total Emission Reduction**	Electric Power Reduction	Petroleum Reduction	Other
233.1	6.7	-12.2	10.6	8.3	4.0	-16.6	10.6	10.0

Besides, the total electricity bills for consumers shift (Figure 4-7). Along with higher electricity consumptions in all scenarios relative to the Reference scenario, the electricity prices are also higher (see Figure 4-8 for details), pushing increasing electricity bills across the scenarios. In 2050, EV mandates increase the electricity bills by 3.6%, 8.3%, and 12.2%, respectively, for the EV25, 50, and 75 scenarios. Adding V2G options reduces electricity prices, thus reducing the total electricity bills by 1.2 percent with the EV25 mandates and about 0.9 percent with the EV50 mandates.

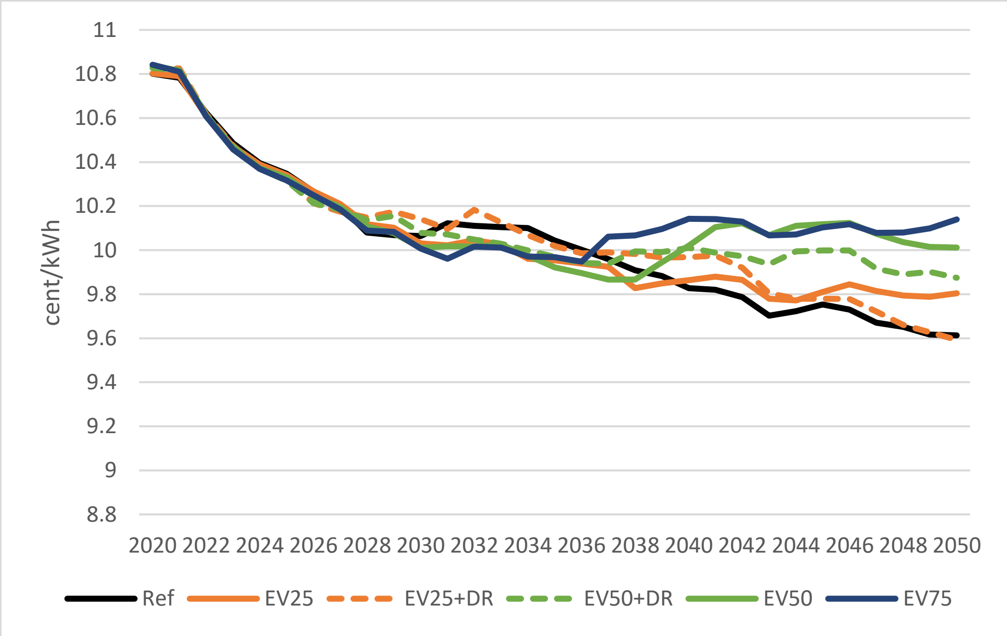


Figure 4-8 SERC-S: Electricity prices by year and scenarios

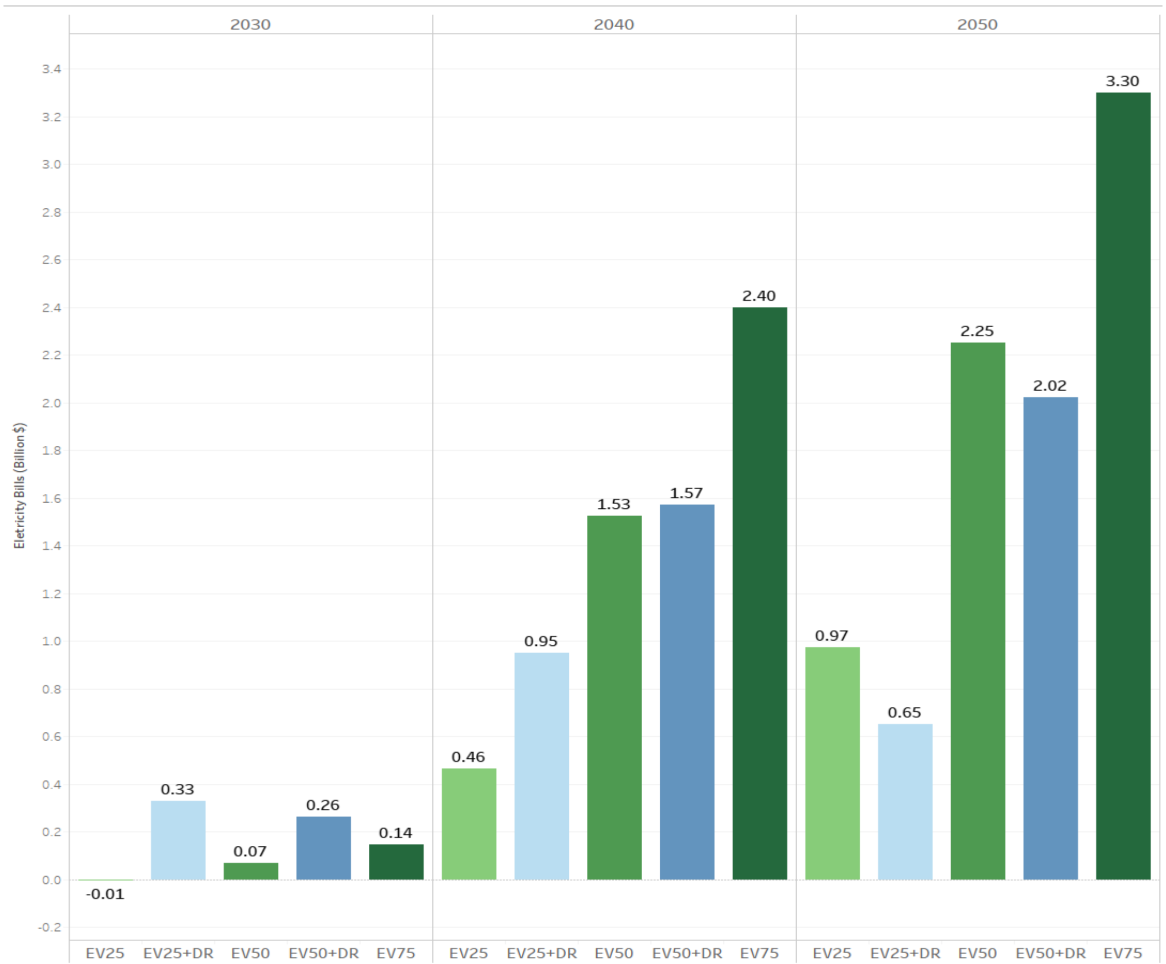


Figure 4-9 SERC-S: electricity bills relative to the Reference in 2030, 2040, and 2050

4.5.6 Regional case study –NYISO

Unlike the SERC-S and the national average, NYISO has a unique generation fuel mix that relies more on fossil fuel to generate electricity (Figure 4-10). In the Reference scenario, coal generation is reduced from 2.2% of the total generation fuel mix in 2030 to 1.0% in 2050. In contrast, natural gas generation is expanding dramatically to 72.8 billion kWh per year, accounting for 49.7% of the total electricity generation. Besides, hydro, solar, and wind play significant roles of 19.3%, 11.2%, and 5.3% respectively in 2050.

Overall, the projected effects of ZEV mandates are phenomenal for NY-ISO. Unlike the national trends, 6.4 Billion kWh of extra nuclear generation is maintained in all policy scenarios showing a 23.4% uptake than the Reference scenario. Besides, coal is retired entirely to 0% by leveraging the extra demand, mostly by natural gas and solar.

ZEV mandates also work differently in terms of the total electricity generation and the generation fuel mix. Despite consistent coal retirement and nuclear uptakes, different scenarios show vast ranges of natural gas generation. In 2050, 7.83 billion kWh natural gas generation is forecasted for the EV50 scenario, which takes 55.9% of the total extra demands. In contrast, in the EV75 scenario, natural gas generation increases by 2.47 billion kWh relative to the Reference scenario. One of the important reasons behind this phenomenon reflects the price elasticity when the EV mandates push the electricity price higher (Figure 4-11), reducing the total electricity demands. Another factor contributing is inter-regional electricity trade and transfer, which makes the generation deviates from the regional total electricity demands. For example, for the EV50 scenario, in 2050 at NYISO, GT-NEMS reports 160.9 billion kWh demands but only 157.9 billion kWh generation showing the imports of 2.9 kWh. This deviation exists for all regions but becomes prominent for the NYISO because the region heavily relies on other regions to provide electricity and the small magnitude between the electricity generation of different scenarios.

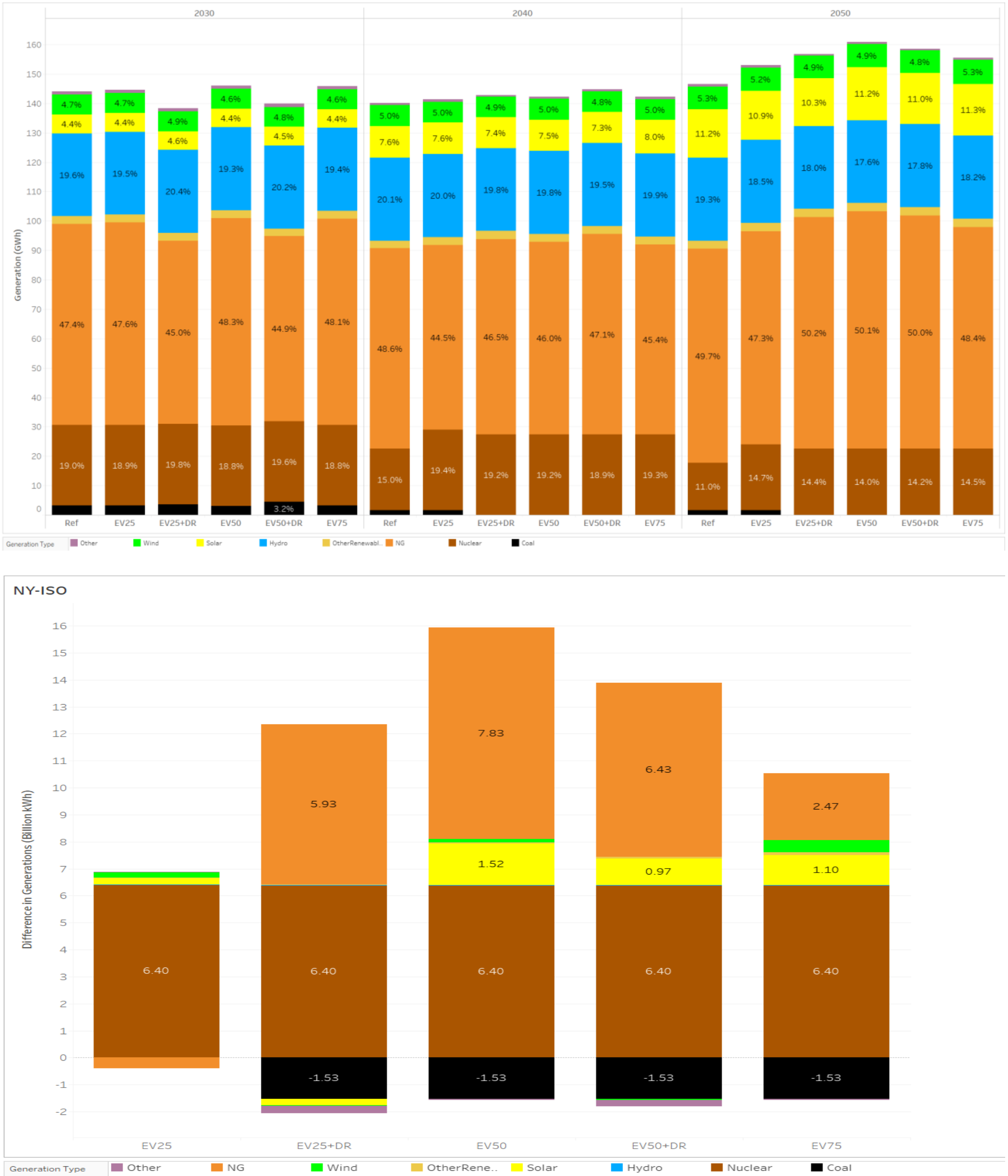


Figure 4-10 NYISO: generation by type in 2030, 2040, 2050 (above) and differences relative to the Reference (below)

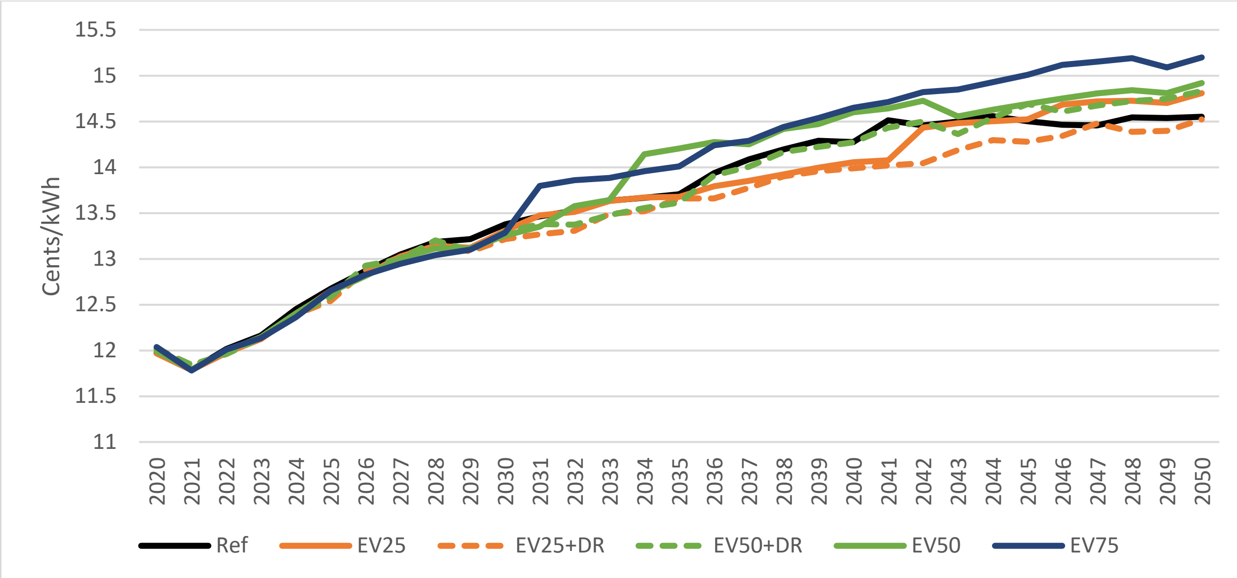


Figure 4-11 NYISO: electricity prices by scenarios

These factors also affect the generation portfolio when adding V2G options. Theoretically, V2G plus EV mandates scenarios should increase the demands because of its lower electricity prices. However, the existence of inter-regional trades may change the effects. For example, compared to the EV50, adding the V2G option increases the regional demands by 0.5% but reduces the regional generation by 1.4%. Correspondingly, the generation fuel mix is projected to leverage about 1.4 billion kWh natural gas less and 0.55 billion kWh solar generation.

The regional emission will be directly based on the regional generation portfolio. Accordingly, the carbon dioxide emissions differ among different scenarios (Table 4-4). Compared to the overall emissions of 197.3 million metric tons in the Reference scenario in 2050, total emission reductions are about 2.6% and 3.2% for the EV50 and EV75 scenarios. The results mostly reflect the energy usage shift from transportation petroleum. Since the EV50+V2G scenario has less regional electricity generation, as shown in Figure 4-8, the V2G option decreases the emissions from the regional electric power sector, therefore, increasing the overall carbon emission benefits.

Table 4-4 NYISO: the carbon dioxide emission reductions in 2050 (million metric tons)

Ref	EV50				EV50+DR			
Total Emission	**Total Emission Reduction**	Electric Power Reduction	Petroleum Reduction	Other	**Total Emission Reduction**	Electric Power Reduction	Petroleum Reduction	Other
197.3	5.2	-1.8	7.8	-0.9	6.4	-0.6	7.8	-0.8

Overall, due to the increase in electricity demand and slight shifts in electricity prices, the electricity bills for the consumer in NYISO increase over time. The rise in electricity bills is higher for more stringent EV mandates. In 2050, we forecast the electricity bills to grow by 4.5%, 9.74%, and 16.1% in the EV25, 50, and 75 scenarios compared to the Reference scenario. However, coupling the V2G options lowers the electricity price, reducing the overall bills slightly by 0.5 and 0.1 percent of the total bills in the Reference scenario.

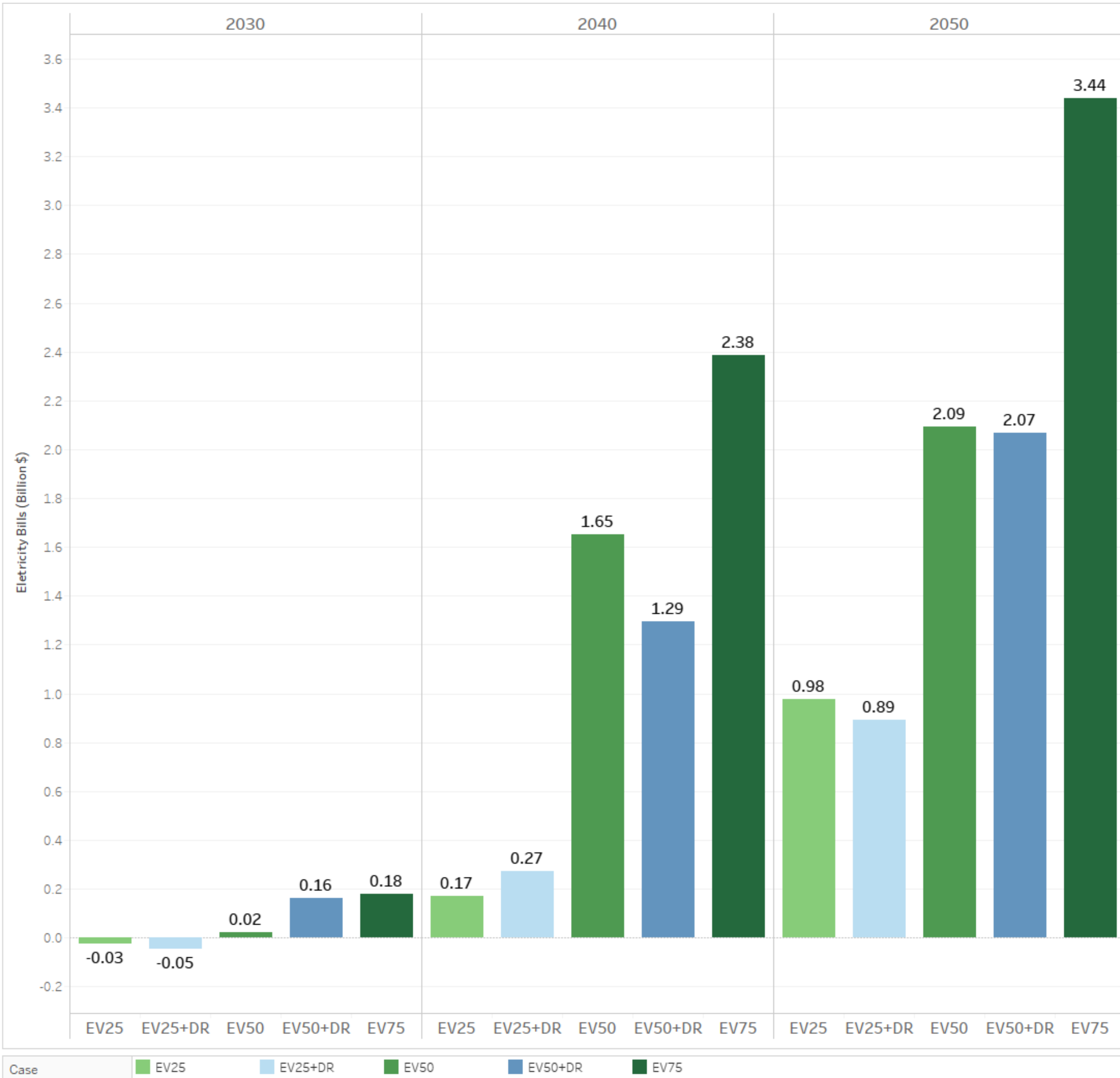


Figure 4-12 NYISO: electricity bills relative to the Reference in 2030, 2040, and 2050

4.5.7 Regional case study – Cal-ISO

California is the research subject for many sustainability studies due to its critical role in leading the national energy green transitions. In the Reference scenario, the region expands its renewable electricity, especially solar and geothermal, dramatically from 2030 to 2050. Relative to 2030, in 2050, Cal-ISO increases its solar generation by 87% and geothermal generation by 64%. In contrast, wind generation and natural gas generation are relatively steady, with 4% and -6% change over 20 years from 2030 to 2050. Overall, renewable energy accounts for 78% of the regional electricity generation in 2050.

ZEV mandates cast extra electricity demand, met mainly by the generation from solar, wind, and natural gas (Figure 4-13). Since the region already has a similar ZEV mandate included in the Reference scenario, the EV25 scenario is projected to have limited impacts. As the requirements become more stringent, more generation is expected. For example, In 2050, the total electricity demands are expected to grow by about 2.5%, 6.9%, and 10.1%, respectively, for the three EV mandate scenarios relative to the Reference scenario. The fuel mix for this extra electricity demand is primarily natural gas, solar, and wind. In 2050, for the EV50 scenario, the demands are met 40.6% by natural gas, 14.8% by solar, and 9.4% by wind.

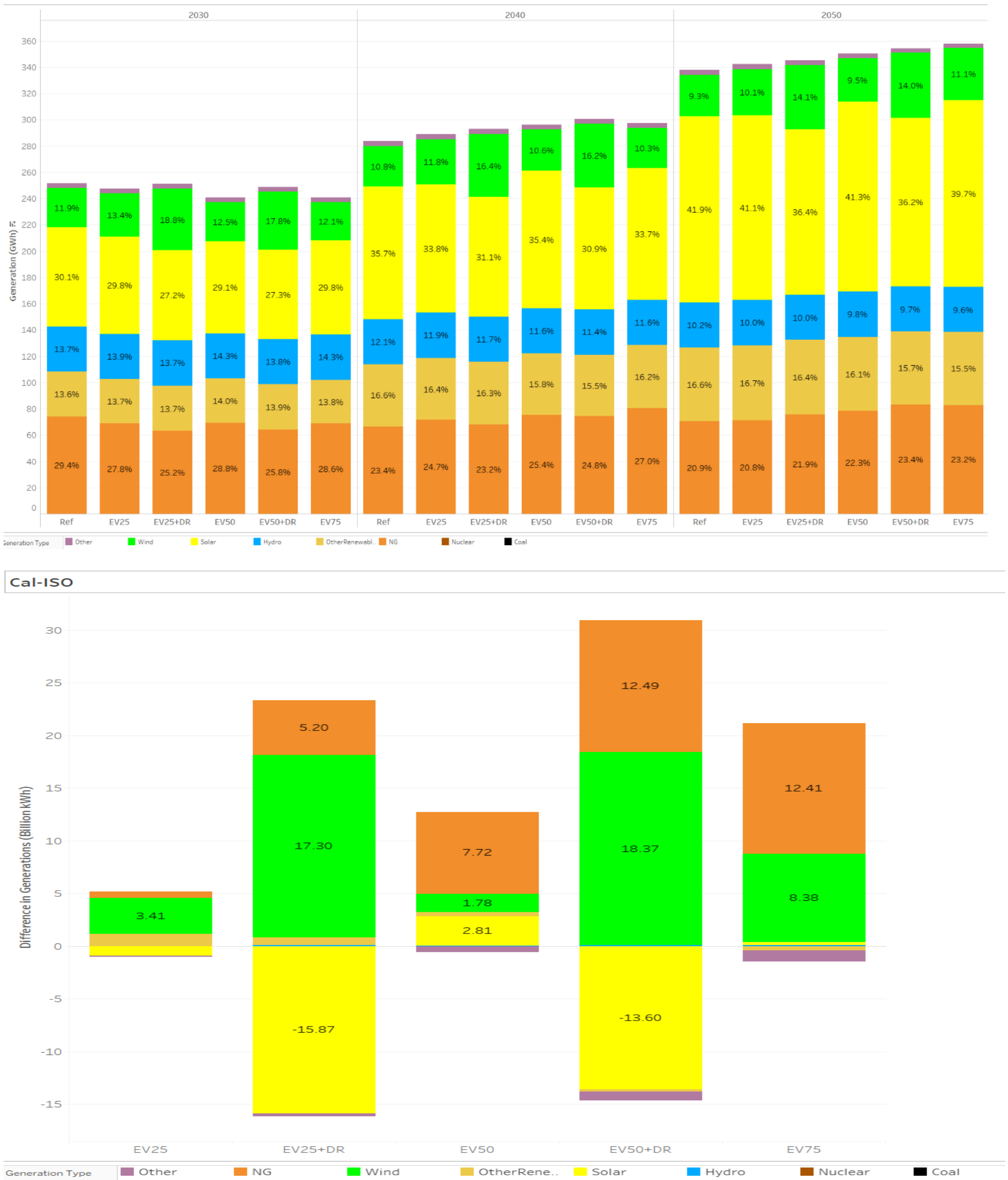


Figure 4-13 Cal-ISO: generation by type in 2030, 2040, 2050 in total (above) and differences relative to the Reference (below)

Adding the V2G option increases the total electricity consumption due to the lower electricity prices (Figure 4-14). With the V2G, the electricity prices are lower than the Reference scenario (see the dash lines in Figure 4-14). Thus, the lower prices incentives more electricity consumption. However, in EV mandates plus V2G scenarios, the generation fuel mix differs from the ones without the V2G. Natural gas and wind increase dramatically while the generation from solar is reduced relative to the Reference scenarios. This phenomenon reflects the intermittency nature of the regional wind and solar resource availability. When given demand-response resources, Cal-ISO's least-cost path shifts some of the electricity generation to wind from solar. For example, in the EV50 scenario, adding V2G reduces 11.4 % of the generation from solar but boosts 50% growth in the wind generation and 6.1% growth in natural gas generation. As a result, the share of solar in the fuel mix shrinks from 43.3% in the EV50 scenario to 36.2% in the EV50+V2G scenario, while the share of wind increases from 9.5% to 14.0%.

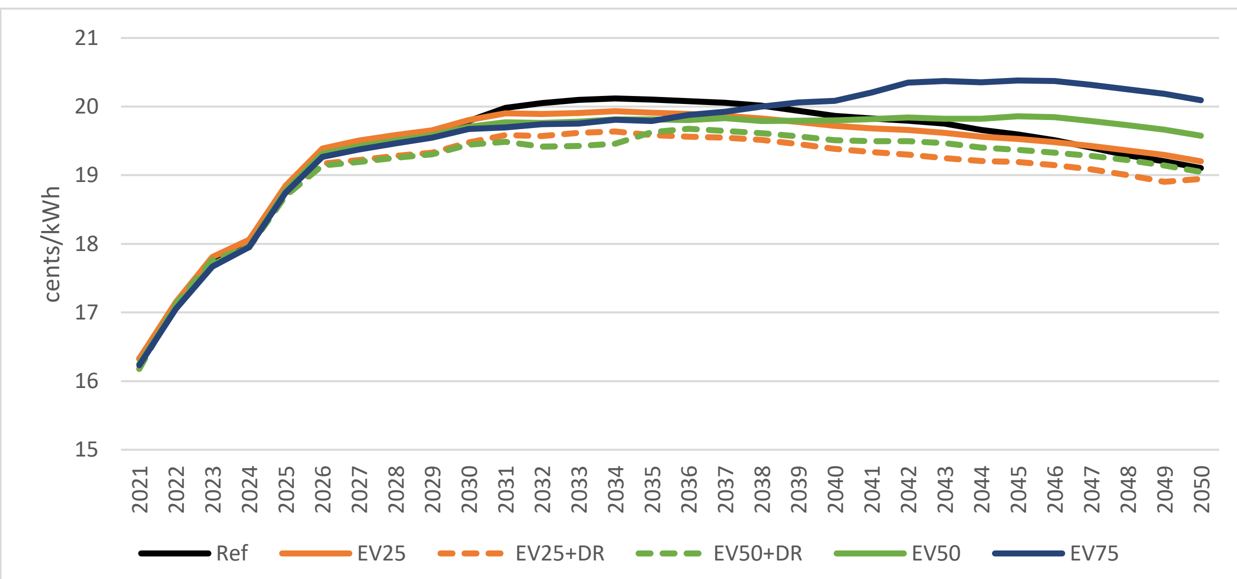


Figure 4-14 Cal-ISO: electricity prices by scenarios

Due to the increase in total electricity generation, the carbon dioxide emission of the electric power sector increases (Table 4-5). However, the saving from petroleum outweighs this increase. Compared to the overall emissions of 319.0 million metric tons in the Reference scenario in 2050, total emission reductions are about 3.3% for the EV50 scenarios. Since the EV50+V2G scenario increases the generation from natural gas, the V2G option increases the emissions from the regional electric power sector, decreasing the overall carbon emission benefits to 8.9 million metric tons in 2050, roughly 2.8% of the total carbon dioxide emissions in the region.

Table 4-5 Cal-ISO: the carbon dioxide emission reductions in 2050 (million metric tons)

Ref	EV50				EV50+DR			
Total Emission	**Total Emission Reduction**	Electric Power Reduction	Petroleum Reduction	Other	**Total Emission Reduction**	Electric Power Reduction	Petroleum Reduction	Other
319.0	**10.6**	-3.3	12.8	1.2	**8.9**	-4.7	12.7	0.9

In the EV mandate scenarios without the V2G options, with the increase in electricity prices and electricity consumption, the electricity bills for the consumer increase compared to the Reference scenario. The rise in electricity bills is higher for more stringent EV mandates. In 2050, we forecast the electricity bills to grow by 3.3%, 9.6%, and 16.1% in the EV25, 50, and 75 scenarios compared to the Reference scenario. Coupling the V2G options introduce two opposite forces on the impacts of the bills – it lowers the electricity price but stimulates higher consumptions. The overall effects differ from scenarios. EV25+V2G scenario ends up escalating 0.6 percent of total electricity bills in the Reference scenario while adding the V2G scenario to EV50 shrinks 1.5 percent of total bills.

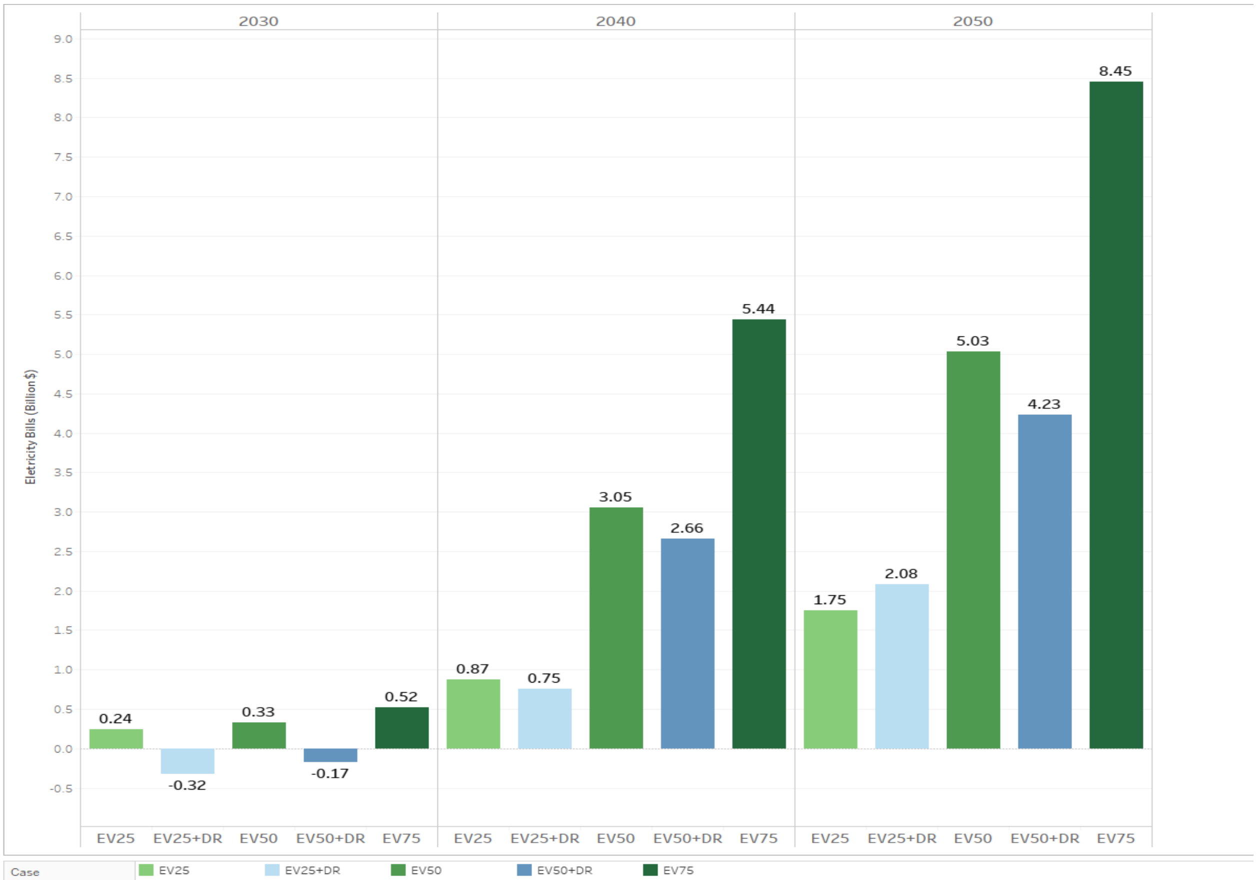


Figure 4-15 Cal-ISO: electricity bills relative to the Reference in 2030, 2040, and 2050

4.6 Discussions and Policy Implications

4.6.1 Conclusions

This study uses GT-NEMS to simulate the long-term macro-economic impacts of a national ZEV policy with and without the V2G options. In sum, for the U.S., the whole society benefits from the ZEV mandates. In the EV50 scenario, the societal benefits reach 74.9 billion $ per year, roughly 0.37% of the national GDP in 2018. Since the electricity bills are treated as welfare transfers, the net society benefits primarily reflect the trade-off between the costs in the electric power sector and the petroleum savings. Both the electric power sector and the consumer become better-off. The electric power sector gains 27.5% of the net benefits, and the rest goes to the end-users. Meanwhile, the ZEV mandates achieve the goal of the carbon dioxide emissions by 164.6 million metric tons. The carbon emission reduction reflects the trade-off between the fuel mix and the petroleum usage and also takes rebound effects from the other end-use sectors into considerations.

Besides, adding V2G to the scope further boosts the societal benefits and emission reductions by 11.8% and 2.6%. The primary reason behind the societal savings is that by providing cheap demand response resources, the generation fuel mix has the option to reduce its costs further. However, some of the savings from fuel switching are compensated because of the rebound effects from electricity consumption when the electricity prices are lower. In sum, the overall effects for the U.S. show positive savings and carbon emission reductions.

Table 4-6 the U.S.: summary of the societal benefits and carbon emission reductions in 2050

EV50			
Electric Power	Additional Cost	TRC	19.8
	Additional Income	Electricity Bills	40.4
	Net Benefits		**20.6**
Consumers	Additional Cost	Electricity Bills	40.4
	Additional Income	Petroleum Bills	94.7
	Net Benefits		**54.3**
Total Society Net Benefits			**74.9**
Total Society Carbon Emission Reductions (MMst)			**164.6**
EV50 + V2G			
Electric Power	Additional Cost	TRC	10.8
	Additional Income	Electricity Bills	34.6
	Net Benefits		**23.8**
Consumers	Additional Cost	Electricity Bills	34.6
	Additional Income	Petroleum Bills	94.6
	Net Benefits		**60.0**
Total Society Net Benefits			**83.8**
Total Society Carbon Emission Reductions (MMst)			**168.9**

Note: the unit in the table is 'billion 2017$' unless otherwise stated.

The study confirms the regional heterogeneities, demonstrating that the impacts of ZEV mandates and the V2G technologies vary by region. First, the net benefits electric power sector vary across regions. Among the three regions, for the EV50 scenario in 2050, SERC-S receive the least net benefits of 0.89 billion $, equating to 6.8% of the TRC in the Reference scenario compared to 10.0% in Cal-ISO and 24% in NYISO. The regional differences reflect the abilities of the regions to manage their resources and shift the costs to consumers. Furthermore, adding V2G options influence the net benefits differently due to its various impacts on fuel mix and electricity bills. For example, in SERC-S, the V2G options decrease the electricity bills primarily due to lower electricity prices and the total resource costs due to the fuel mix shifts. However, in Cal-ISO, the

V2G options increase the electricity bills and the total resource costs primarily due to rebound effects from electricity consumption.

Second, the consumer net benefits are positive for all regions in 2050 due to considerable savings from avoided petroleum usages. However, the magnitudes of the savings reflect the relative size of the energy usage from the transportation sector to the electric power sector.

Overall, the regional total net benefits are positive but differ by region. In 2050, for the EV50 scenario, NYISO has the most significant savings, 7.96 billion$, primarily due to its considerable regional response in the electrification of the transportation sector, followed by SERC-S with 3.82 billion$ and Cal-ISO with 3.65 billion$. The impacts of adding the V2G options also show regional heterogeneous results. By offering the possibilities to reduce costs, the societal benefits increase by about 0% in NYISO, 2.3% for SERC-S, 22.2% for Cal-ISO, indicating the regional disparities in absorbing the demand-response resources effectively.

The overall net impacts in CO_2 emissions differ by region, showing the heterogeneous regional situations in the direct emission reductions in petroleum, indirect emissions from electricity generation, and induced macro-economic impacts, notably rebound effects. In 2050, we estimate the societal net carbon emissions impacts of the EV50 scenario vary - 6.68 million metric tons in SERC-S, 5.21 million metric tons in NYISO, and 10.62 metric tons in Cal-ISO. Adding V2G options does not necessarily reduce the overall carbon emission since the rebound effects exist. For example, in 2050, adding V2G to the Cal-ISO EV50 scenario reduces the comprehensive net carbon emission benefits from 10.6 million metric tons to 8.96 million metric tons primarily due to the overconsumption stimulated by the low electricity prices.

Table 4-7 SERC-S.: summary of the societal benefits and carbon emission reductions in 2050

EV50			
Electric Power	Additional Cost	TRC	1.36
	Additional Income	Electricity Bills	2.25
	Net Benefits		**0.89**
Consumers	Additional Cost	Electricity Bills	2.25
	Additional Income	Petroleum Bills	5.18
	Net Benefits		**2.93**
Total Society Net Benefits			**3.82**
Total Society Carbon Emission Reductions (MMst)			**6.68**
EV50 + V2G			
Electric Power	Additional Cost	TRC	1.21
	Additional Income	Electricity Bills	2.02
	Net Benefits		**0.81**
Consumers	Additional Cost	Electricity Bills	2.02
	Additional Income	Petroleum Bills	5.18
	Net Benefits		**3.16**
Total Society Net Benefits			**3.97**
Total Society Carbon Emission Reductions (MMst)			**3.95**

Note: the unit in the table is 'billion 2017$' unless otherwise stated.

Table 4-8 NYISO: summary of the societal benefits and carbon emission reductions in 2050

EV50			
Electric Power	Additional Cost	TRC	0.79
	Additional Income	Electricity Bills	2.41
	Net Benefits		**1.60**
Consumers	Additional Cost	Electricity Bills	2.43
	Additional Income	Petroleum Bills	8.79
	Net Benefits		**6.34**
Total Society Net Benefits			**7.96**
Total Society Carbon Emission Reductions (MMst)			**5.21**
EV50 + V2G			
Electric Power	Additional Cost	TRC	0.79
	Additional Income	Electricity Bills	3.36
	Net Benefits		**2.59**
Consumers	Additional Cost	Electricity Bills	3.47
	Additional Income	Petroleum Bills	8.79
	Net Benefits		**5.32**
Total Society Net Benefits			**7.91**
Total Society Carbon Emission Reductions (MMst)			**6.42**

Note: the unit in the table is 'billion 2017$' unless otherwise stated.

Table 4-9 Cal-ISO: summary of the societal benefits and carbon emission reductions in 2050

EV50			
Electric Power	Additional Cost	TRC	2.85
	Additional Income	Electricity Bills	5.03
	Net Benefits		2.18
Consumers	Additional Cost	Electricity Bills	5.03
	Additional Income	Petroleum Bills	6.50
	Net Benefits		1.47
Total Society Net Benefits			**3.65**
Total Society Carbon Emission Reductions (MMst)			**10.62**
EV50 + V2G			
Electric Power	Additional Cost	TRC	2.03
	Additional Income	Electricity Bills	4.23
	Net Benefits		2.20
Consumers	Additional Cost	Electricity Bills	4.23
	Additional Income	Petroleum Bills	6.49
	Net Benefits		2.26
Total Society Net Benefits			**4.46**
Total Society Carbon Emission Reductions (MMst)			**8.96**

Note: the unit in the table is 'billion 2017$' unless otherwise stated.

4.6.2 Policy implications

First, the study confirms that a national ZEV mandate is projected to reduce carbon dioxide emissions and incur negative costs to society while making both the electric power and consumers better off. Notably, when adding V2G to the picture, the benefits increase. The findings convey a critical and clear message to the policymakers to take similar policies into considerations and examine the details.

Meanwhile, our model also reveals that at a macro-economic scope, the impacts of the EV sales mandates exceed the scope of the transportation sector, electric power sector, influencing many end-use consumers through indirect and induced effects. It indicates the need for policymakers to move beyond sectoral narratives and adopt a holistic and systematic view.

Another implication from the macro-economic level perspectives is that one policy alone, such as a national ZEV mandate, cannot achieve profound decarbonization goals. Without further decarbonization of the electric grid and energy efficiency promotions, the net society carbon emission reductions shrink as more emissions occur during the electricity generation or due to rebound effects. Our study forecasts less than 5% total carbon emission reductions from the EV50 scenario, which is not optimal for many states' goals to deep cut their carbon emissions. Thus, a set of various green policies, especially the ones promoting cleaner electricity production and energy efficiency, would provide synergistic effects, helping society fight climate change effectively and affordably.

Second, close scrutiny at the national level reveals many equity concerns. Our model projects the electric power sector and the consumers as a whole receive positive net benefits from ZEV mandates. However, the study shows regional heterogeneities in their response to EV penetration and V2G technologies. The macro-economic analysis echoes the conclusions from the sectoral analysis (see Section 3.4.2). The regional situations, including the regional resource availability and the price-elasticities of electricity, contribute to the distinct regional response to the nationwide universal EV mandates. For example, the three regions all differ from the national trends in the generation fuel mix change and shifts in the end-user sectoral response.

Regional heterogeneities may raise potential equity issues resulting when different regions face a similar level of ZEV mandates from a higher level of the government, for example, the state coalitions or the federal. Across different regions, both the costs and the effects of carbon emission reductions can be different. Thus, if universal legislation or regulation is implemented, the benefits and the burdens would be distributed unevenly among different regions. This finding confirms the existence of this phenomenon in EV mandate policies, which requires further research.

4.6.3 Limitations and future directions

Several limitations arise from the main modeling framework, GT-NEMS. First, we have acknowledged that the way we modeled V2G is not optimal but offers a reasonable but not complete proximation. GT-NEMS pre-sets a regional vehicle-type electricity demand curve for all the years, limiting the efforts of modeling direct EV charging behavior changes. Our analysis treats V2G as a cheap demand-response resource, allowing electric vehicles to serve a similar function as the storage in the perspective of the electric power operations. However, the revenue from the approximated "storage" does not feedback to the consumers to incentive EV adoptions. Thus, a more rigorous effort covering broader aspects of the business model considering the consumer-grid partnership is needed in the future.

Another limitation from the GT-NEMS is the challenges in the explainabilities and sensitivity analysis, similar to almost all CGE and other integrated computational ex-ante models. Based on I/O model frameworks, the macro-economic models are extremely complex and inter-connected. Adopting the systematic view, the model makes it difficult to ex-post examine one single factor's impacts. In addition, GT-NEMS does not embed sensitivity analysis in the framework. Thus, the work in this study provides the estimates without confidence intervals or uncertainty ranges, limiting the validity of the conclusions made.

This could be improved by running the models with more side cases with certain variables in the inputs or assumptions. However, the process can be time-and resource-consuming since a single cycle of the GT-NEMS model can take days to complete. Another possible solution is to run a series of side cases to examine one factor's sensitivity. However, this solution is seldom adopted or even acceptable due to the model's time- and resource-consuming nature of the model. Another solution is to apply "meta-modeling" using ex-post econometric models to increase the explainabilities of the models (Brown et al., 2020). In the future, more explanatory work is needed to verify the validity of these solutions and improve the understanding of the policies.

Last, this study only covers national ZEV mandates, one set of EV promotion policies. More policy alternatives are on the agenda to discuss in the academic and policy arenas. Some examples include other non-market incentives such as direct EV infrastructure investments and many market-based measures, such as EV purchase tax credits. These policies should be analyzed in future studies to facilitate a full picture of the alternative policy tool options.

CHAPTER 5. CONCLUSIONS

5.1 Summary of findings

This dissertation provides empirical evidence and contributes to the quantification framework by filling some of the missing puzzles unsolved to tackle today's green transitions. The study conducts more systematic and comprehensive evaluations of the co-benefits and co-costs from various perspectives, demonstrating case studies on different sectors and scopes (air quality and health, sectoral and macroeconomic activities). The three chapters in this dissertation analyze distinct aspects and aim to answer research questions in each area (Table 3-1).

In the first study, I evaluate the impacts of relaxing energy policies under the Trump administration on U.S. ozone control. The integrated model simulations show that compared to a scenario of continued EPs and stationary climate, relaxation of EPs coupled with intense warming will increase the number of U.S. counties in ozone nonattainment (NNA) by >75% in 2050. The NNA under the current standard of 0.07 parts per million (ppm) is projected to increase in 2050 from 27 to 49, while NNA under a tighter standard of 0.06 ppm will increase from 497 to 879. The monetized national annualized additional health costs are \$2.49 billion for RCP8.5, \$2.47 billion for RCP4.5, and \$2.30 billion without climate change, respectively. Overall, the study demonstrates synergistic effects of EP relaxation with climate change on ozone standard compliance and indicates that the current decline in ambient ozone could be reversed by relaxing EPs in a changing climate.

In the second study, I explore the short-term, sectoral co-benefits and co-costs from the EV adoption policies on electricity grid operations in three regions – SERC-S, NY-ISO and Cal-ISO. I show that in the scenarios of 12.5, 25, and 37.5 percent EV penetration, the increases in demands due to EV charging needs are substantial. The O&M costs increase and disproportional higher than the increase in the electricity demand, escalating the operational costs per generation. The model also projects significant carbon emission reductions, primarily due to the avoided gasoline usage in all regions. In addition, the results indicate substantial regional heterogeneities. Among the three areas, SERC-S has the most significant EV charging loads with the lowest additional costs increased per generation. By contrast, even with minor demands from EV charging, NY-ISO has higher operational cost additions due to its lack of cheap resources other than combustion turbines to serve EV charging needs. The CO_2 emission reductions resulting from EV adoptions also show regional differences. SERC-S has the most significant CO_2 emission reductions in the EV37.5 scenario but lower than Cal-ISO at the lower level of EV penetration. Due to its relatively smaller needs from EV and high reliance on the less efficient combustion turbines compared to NGCC plants, NYISO has the smallest amount of CO_2 emission reduced – 1.16 million metric tons, 2.32 million metric tons, and 3.48 metric tons in 2030.

In the third study, I use GT-NEMS to simulate the long-term macro-economic impacts of a national ZEV policy, with or without the V2G options. In sum, for the U.S., the whole society benefits from the ZEV mandates. In the EV50 scenario, the societal benefits reach 74.9 billion $ per year in 2050, roughly 0.37% of the national 2018 GDP. Besides, adding V2G to the scope further boosts the societal benefits and emission reductions by 11.8% and 2.6%. However, some of the savings from fuel switching are compromised because of the rebound effects from electricity consumption when the electricity prices are lower. Last, the study forecast positive net benefits for all regions, but the magnitude differs substantially by region. In 2050, for the EV50 scenario, NY-ISO has the most significant savings, $7.96 billion, primarily due to its considerable savings in the electrification of the transportation sector, followed by SERC-S with $3.82 billion and Cal-ISO with $3.65 billion. The impacts of adding the V2G options also show regional heterogeneous results. By offering the possibilities to reduce costs, the societal benefits increase by about 0% in NY-ISO, 2.3% for SERC-S, 22.2% for Cal-ISO, indicating the regional disparities in absorbing the demand-response resources effectively.

5.2 Contribution to research

Cost-benefit analysis is a widely-used crucial tool for governmental agencies. The validity of the cost-benefit relies on the systematic and comprehensive understanding of the co-benefits and co-costs associated with the public policies. Despite the consensus of necessities and the significance of understanding the co-benefits and co-costs, we still don't have a complete picture or a thorough understanding of the broader impacts of public policies on energy and environmental, especially carbon mitigation policies. Furthermore, the recent developments from the governments worldwide have attracted more attention to revisiting the concepts.

This dissertation expands on research in the energy and environment policy by providing better empirical evidence and systematic quantification frameworks. In general, this study highlights critical relationships in intricate modeling systems, thereby enabling insights that might otherwise be obfuscated or overlooked. By applying complex integrated models of energy policies, climate systems, and health evaluations, policymakers can better understand the complexity of features that influence policy markets in the energy-related economy.

Table 5-1 Summary of research questions and findings

Area	Research questions	Summary of findings
Environmental Impacts	What are the impacts of relaxing energy policies on the attainability of ozone standards, considering the synergistic influence of climate change?	The continuation of the EP policies significantly eases the difficulties of ozone standard attainment. The synergistic effect of the energy policies with climate change exists – under the situations of more aggressive climate change, EP policies will have higher benefits in ozone standard attainment, thus reducing overall health costs.
Sectoral-economic Impacts	What are the influences of electric vehicle charging demand on short-term grid operation cost for Southern company territory, New York ISO, and California ISO?	In the short term, the policy-driven electric vehicle penetration increases the operation cost for the grid.
	Correspondingly, what are the influences of electric vehicles on CO_2 emissions from the electric power sector and the transportation sector?	In the short term, the policy-driven electric vehicle penetration increases the CO_2 emissions from the electric power sector but reduces more CO_2 emissions from the transportation sector, thus decrease the overall net CO_2 emissions.
Macro-economic Impacts	What are the influences of massive adoptions of electric vehicles on grid operational costs and CO_2 emissions in the long term?	In the long run, capacity planning enables policy-driven electric vehicle penetration to lower CO_2 emissions and total costs.
	What are the influences on rates and consumer bills for residential, commercial, industrial, and transportation sectors, respectively?	The policy-driven electric vehicle penetration decreases the electricity rates for all sectors as the utilities lower their grid operational costs, thus reducing the electricity bills for the end-use sectors.
	What are these influences on grid management and consumer bills changed by coordinated charging and other ancillary services?	The policy-driven electric vehicle penetration decrease operation costs and consumer bills, which are further reduced by introducing EV-grid partnerships to allow coordinated charging and ancillary services from grid-EV integrations

In the first study, my research confirms the significance of continuing the EP policies on ozone standard control and achieving better public health. Although ground-level O_3 in the U.S. has seen a substantial decline over the last several decades due to enduring emission mitigation efforts, our assessment suggests that a continuing decline in the O_3 should not be taken for granted. In addition, it also evaluates the magnitude of the synergistic effect between the energy policies with climate change. It calls for closer scrutiny of the relationship between energy policies and climate change mitigation efforts. As the world's largest economy and the second-largest emitter of CO_2, the United States plays a leading role in the international community catalyzing cooperation on climate change. The 2014 U.S.-China joint announcement on climate goals, for example, helped set the stage for the success of the United Nations Climate Conference in Paris, encouraging 190 other countries to put forward climate actions of their own. A relaxation of EPs by the United States chills these global actions, with broad implications for climate. The magnitude of this synergistic effect demonstrates the critical need to conduct assessments of EPs in the context of the global climate system when evaluating the resulting impacts on local air quality and associated health benefits/disbenefits.

The second study indicates the design of the EV-related policies, especially its policy evaluations, requires holistic views combining the power sector, the EV drivers, and other stakeholders into considerations. Estimating the policy impacts requires systematic modeling, often resulting in non-linear results over the stimulus. Overall, the study demonstrates that to achieve CO_2 emissions reductions with low cost, the electric power sector needs advanced plannings for EV charging than its current practice of unit commitment and traditional operations. The EV charging demands may be carbon-intensive resources with relatively low efficiency, such as the oil and gas turbines, leading to increases on average CO_2 intensity of the grid. Even though the overall CO_2 emissions are reduced due to the reductions in transportation gasoline usage, the EV penetration put pressure on grid operations by increasing operational costs and causes difficulties for the power sector to achieve the sectoral goals of carbon emission reductions. Last, this study confirms the existence of regional heterogeneities in EV policy responses, raising inter-regional equity concerns.

In the third study, the findings reveal that at a macro-economic scope, the impacts of the EV sales mandates exceed the scope of the transportation sector and the electric power sector, influencing many end-use consumers through indirect and induced effects. Overall, it indicates the need for policymakers to move beyond sectoral narratives and adopt a holistic and systematic view. A national ZEV mandate is projected to reduce carbon dioxide emissions and incur negative costs to society while making both the electric power and consumers better off. Notably, when adding V2G to the picture, the benefits increase. The findings convey a critical and clear message to the policymakers to take similar policies into considerations and examine the details. A set of various green policies, especially the ones promoting cleaner electricity production and energy efficiency, would provide synergetic effects, helping society fight climate change effectively and affordably. Last, the study demonstrates that at both national and regional levels, many equity concerns need to be addressed, showing the benefits distribute unevenly for different individuals within and inter-regions.

5.3 Future work

Moving forward, this dissertation needs more work in the future to improve the theoretical soundness and inform better policy implications. First, advancing the research on environmental impacts of energy policies, a potential future approach would incorporate more abatement costs demonstrations to form a complete cost-benefit analyzing framework. The current work in Chapter 2 examines the consequences of relaxing the environmental policies but lacks illustrations on the potential technological or policy-driven measures to tackle the problem. The costs to implement these measures would provide a critical message to form a thorough picture for the policy designs. Thus, I hope to continue the work and dig deeper to connect the work to inform the cost-benefit analysis in environmental policies better.

Expanding the work on short-term, sectoral-focused EV policies case study, one of the most critical challenges needed addressing is how to adopt a dynamic view on consumer behaviors. Unlike the static view used in Chapter 3, the EV owners do not entirely make their decisions exogenously. Their decisions on driving and charging their vehicles are adaptive and situation-sensitives influenced by many surrounding factors, such as the accessibility of EV infrastructure and the availability of public transit. Many recent studies have started to fill the blank on these directions, digging deeper into the factors affecting consumer decision-making. In the future, we need more research to understand the behavioral aspects to move beyond the linear interpolation from the status quo.

In addition, addressing the grid's potential reliability concerns, I hope to incorporate more reliability evaluation metrics into the current study. Mainly focused on the cost-effectiveness and sustainable aspects of the electric power grid, the study in Chapter 2 does not fully consider the grid reliability. One of the most critical functions of electric power utilities is to maintain a reliable grid, and recent events, such as the Texas blackout in 2021, have attracted more attention. I hope to evaluate the impacts of massive electric vehicle adoptions on the reliability of the grid. To carry out this research plan, one direction is to assess how the fluctuations of the demands would change the status of grid operations. Another direction of improvement is to examine the functional reserve for electricity generation.

Many similar efforts are required at the macro-economic level and long-term scope. The model framework used in Chapter 4, GT-NEMS, has several limitations, providing opportunities for future research to proceed. First, I hope to add more behavioral components to model the dynamic and adaptive response possible for the EV drivers. This could also connect to the development of more consumer-utility partnerships and related business models.

To further enhance the explainability of the macro-economic complex systems model, I plan to construct meta-modeling using ex-post econometric models to increase the explainability of the models (Brown et al., 2020). It will assess the impacts from various factors and improve the understanding of the policies, especially at a regional level. Exploring these aspects in future studies would provide insights on deciphering the regional heterogeneities and design more cost-effective policies.

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